Childhood Poverty and Labor Market Outcomes: The Mediating Role of Health and Education*

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Abstract

In the study of the long run effect of childhood poverty, two issues are overlooked. First, the proportion of the total effect of childhood poverty on adult labor market outcomes that passes through mediator covariates is barely studied. Second, many studies considered childhood as a single period and neglected the differences in stages of child development (infancy, early childhood, mid-childhood, and late childhood) for acquiring specific types of skills. Separate analyses for each stage enable us to identify the most critical childhood period. The overall purpose of this paper is to bridge these gaps using data drawn from the Panel Study of Income Dynamics (PSID). The study employs propensity score matching (PSM) and average causal mediation effect (ACME) methods to provide empirical evidence to the overlooked issues. The total effect estimation results show that persistent childhood poverty significantly decreases average annual labor income (by $11,252) and hours worked (by 182.1 hours) whereas it increases the number of weeks unemployed per annum (by 1.96 weeks). The annual labor income causal mediation estimate shows that 42.25 percent of the total effect of childhood poverty passes indirectly through the negative influence of childhood poverty on education and childhood health. Similar figures for hours worked and the number of weeks unemployed are 22.57 and 21.73 percent respectively. The results from the PSM and ACME analyses for stages of child development revealed that early childhood is the most critical period.

Keywords: average causal mediation, labor market outcomes, health, education, childhood poverty

JEL Codes: J13, J24

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1 Introduction

Millions of Americans live on incomes below the federal poverty line, despite the fact that the U.S. is a relatively wealthy country by international standards. In 2019, the U.S. Census Bureau reported that 38.1 million people (or 11.8 percent of the total population) were living in poverty. Moreover, the wealth deprivation is unevenly distributed across different age groups, with the most severe effect manifested on the lowest age group. The same report stated that 16.2 percent of people under the age of 18 (or 1 child out of 6) live in poverty, whereas for the adult counterpart the ratio is 1 adult out of 9. Hence, poverty analysis requires special consideration for children. Furthermore, childhood poverty calls for special deliberation since its effect extends to adulthood and manifests in different forms: educational attainment, health status, labor force participation, and earnings.

Most of the surveyed literature separately analyzed the effect of childhood poverty on health, educational achievement, and late-life labor market outcomes. Ziol-Guest et al. (2012) analyzed the long-run effect of growing up poor on different health outcomes: adult arthritis, hypertension, and activities of daily living (ADL). They found that the report of diagnosis of adult arthritis by children from a family that earns less than $25k per annum (10.6 percent) is significantly larger than that of the non-poor children (4.6 percent). The hypertension report of the two groups is also significantly different, which is 19.0 percent and 11.2 percent, respectively. Their result also showed that a $5,000 increase in household income among low-income children in any of the years between the prenatal period and age 2 (a total of 4 years) is associated with a 1.1 percentage point reduction in the proportion of years that hypertension was reported between the age of 30 and 41 years old. It also showed that there is a 1.3 percentage point reduction in the proportion of years that arthritis was reported and a 0.02 point reduction in the ADL index. Other studies also showed that those who grew up poor experienced deteriorating adulthood physical and mental health due to cumulative underinvestment in healthcare during their childhood (Currie & Almond, 2011; Duncan et al., 1998; Levy & Duncan, 2000)

GPA (Lesner, 2018), years of schooling (Duncan & Magnuson, 2013; Lesner, 2018), and complete HS at the age of 20 and four year college degree at the age of 25 (Ratcliffe, 2015) are the common outcome variables to analyze the effect of childhood poverty on educational achievement. Their findings confirmed the negative effect of childhood poverty on educational achievement. Lesner (2018) demonstrated that individuals who experience childhood poverty are likely to end up with a lower GPA. Furthermore, one additional year of childhood poverty reduces the duration of schooling for the individual (by about 2 months). Ratcliffe (2015) also found that persistently poor children are 13 percent less likely to complete high school by age 20, 29 percent less likely to enroll in post-secondary education by age 25, and 43 percent less likely to complete a four-year college degree by age 25. Furthermore, Duncan and Magnuson (2013) used the official poverty line of $22,000 for a family of four and found that a child from a household with an income below the official poverty line, on average, gets schooling only for 11.8 years. On the other hand, the children from households with an income between one and two times the poverty line and more than twice the poverty line have average schooling years of 12.7 and 14 years, respectively. Similarly, other literature also showed that many children with disadvantaged backgrounds struggle academically and do not complete high school (Chaudry & Wimer, 2016; Dahl & Lochner, 2012; Duncan et al., 1998, 2011; Kubilius & Corwith, 2018; Levy & Duncan, 2000)

Studies also compare different adult labor market outcomes to gauge the long-run effect of growing up poor. These include annual labor income (Cho & Hashmati, 2015; Duncan & Magnuson, 2013; Lesner, 2018; Risky et al., 2019; Ziol-Guest et al., 2012), hourly wage (Ziol-Guest et al., 2012), annual work hours (Duncan & Magnuson, 2013; Ziol-Guest et al., 2012) and employment status (Ratcliffe, 2015). Their findings consistently showed the negative effect of childhood poverty on labor market outcomes. Ziol-Guest et al., (2012) findings revealed that children in low-income families between the prenatal period and age two had lower annual earnings as adults ($21,600) than children from high-income families ($53,400). For similar groups, annual work hours are 1,460 and 1,877 and hourly earnings are $13.60 and $26.50 during adulthood, respectively.

Similarly, Duncan and Magnuson (2013) showed that children who are raised in the three categories of households mentioned earlier have average annual earnings of $17,900, $26,800, and $39,700, respectively, as adults. The annual work hours for adults from the same groups of households are 1,512, 1,839, and 1,963, respectively. Cho and Hashmati's (2015) findings from quantile regression analysis showed that the log wage differential between poor and non-poor groups is observed at the overall distribution of wages from 8 percent to 21 percent. The 6.4 percent adult disposable income reduction (Lesner, 2018) and 87 percent earnings penalty (Risky et al., 2019) findings reinforce the long run negative effect of childhood poverty. Ratcliffe (2015) using employment status as an outcome variable also found that persistently poor children are less likely (by 37 percent) to be consistently employed as young adults than their ever-poor and never poor counterparts. Only 35.4 percent of persistently poor children were consistently employed during ages 25 to 30. This figure is much smaller than the same results for non-persistently poor and never poor children, which are 63.6 percent and 70.3 percent, respectively. Similarly, Other literature found that these children only obtain spotty employment and low earnings as young adults (Gregg et al., 1999; Lesner, 2018; Ratcliffe & McKernan, 2010, 2012).

Bellani and Bia's (2019) analysis is the only exception that examined the interrelated effect of childhood poverty on adult outcomes and mediator outcome (education) with a quantified transmission mechanism. The outcome variables considered in these analyses are income and poverty status indicator dummy. Their findings showed that childhood poverty significantly decreases the level of income in adulthood (average loss of €764) and increases the average probability of being poor (1.5 times more). Moreover, the results revealed the significant role of education in this intergenerational transmission.

In these studies, however, two important issues are overlooked. First, researchers barely studied the role of mediator covariates (health and education) and what proportion of the total effect of childhood poverty on adult outcome passes through these mediator covariates. Second, these studies focus on overall childhood poverty as a single period but neglect the effects of childhood poverty that occurs at different stages of childhood development (the decomposition).

The California Department of Education (2000) reported that both the physical and mental development of children have their own critical periods. This gives some insight into the fact that poverty at different stages of child development (infancy, early childhood, mid-childhood, and late childhood) may have different immediate and long-term impacts. The poverty that occurs during early childhood may not have a similar effect as poverty that occurs during late childhood. For example, Conti and Heckman (2012) showed that parental investment in children's education to learn a second language has a better efficiency before age 12.

Nevertheless, no study, at least in the major literature, has separately analyzed the heterogeneous effects of childhood poverty, which occurs at different stages of child development, on adult outcomes. Furthermore, children who have a similar type of economically disadvantaged background may achieve different levels of success during adulthood. Ratcliffe (2015) found that not all impoverished children have poor young adult outcomes. This indicates that mediator complementary factors that occur between infancy and late adulthood play a significant role to make the child successful or not later in life. The studies surveyed in this paper show the negative effect of childhood poverty on health, education, and different adult outcomes separately. However, no study, at least in the major economic literature, deals with the transmission mechanism that maps the interaction of childhood poverty with mediator factors and adult labor market outcomes by considering education and health as interrelated mediator factors.

The overall purpose of this study is to evaluate the impact of childhood poverty on labor market outcomes in a way that bridges the identified knowledge gaps. In addition to the childhood poverty effect analysis that treats childhood as a single period, poverty incidences that occurred at different stages of child development are studied separately. For both types of analyses, the transmission mechanism from childhood poverty to labor market outcomes through mediator variables are traced and quantified into direct and indirect effects.

To shed light on the issue, I used an estimation strategy that combines propensity score matching (PSM) and average causal mediation effect (ACME) analysis. The propensity score matching estimates the effect of childhood poverty on an individual's health and educational achievement. These outcome variables are used as mediator variables while the second method gauges the effect of childhood poverty on labor market outcomes per annum: labor income, hours worked, and average numbers of weeks unemployed. This method enables us to decompose the total effect of childhood poverty on labor market outcomes into direct and indirect effects. The method also allows dependency between the two mediator factors.

The data for the analyses is drawn from the Panel Study Income Dynamics (PSID) data set. The data set is an inter-generational panel waves since 1968 and it provides detailed information on child health, household-level characteristics, and parental characteristics. Propensity score matching estimation results show a significant and negative impact of childhood poverty on both children's health and educational attainment. The proportion of individuals who had a healthy childhood is significantly lower (by 19.62 percent) for the group who experienced persistent childhood poverty than those who did not. Similarly, the proportion of individuals who have a college degree is significantly lower (by 12.45 percent) for those individuals who had persistent childhood poverty experiences. The same type of comparison in terms of years of schooling outcome variables provides consistent result with the estimation of health and college degree attainment outcome variables.

The study traces the transmission mechanism of childhood poverty to adult labor market outcomes in addition to its effect on the mediator variables. The results from these estimates inform policy-makers about how to tailor interventions that positively influence children's health outcomes and educational achievement that consequently improve their adult labor market outcomes. The average causal mediation analysis results showed that experiencing persistent childhood poverty significantly lowers annual income and hours worked whereas it increases the number of weeks unemployed per annum. The total effect estimation results are annual labor income ($11,252), annual hours worked (182.1 hours), and the number of weeks unemployed per annum (1.96 weeks) differences on average between impoverished and non-impoverished groups. For all the three outcome variables, a significant portion of the total effect of persistent childhood poverty passes indirectly through the two mediator variables: education and childhood health. Out of the total deteriorating effect of childhood poverty on annual labor income, 42.25 percent of it passes indirectly through the negative influence of the poverty on health and educational attainment. The remaining proportion is the direct effect of childhood poverty on labor income. Similarly, hours worked and the number of weeks unemployed receive 22.57 and 21.73 percent, respectively, of the total effect of childhood poverty indirectly through its negative effect on education and childhood health.

The gender disaggregation analysis of the average causal mediation effect (ACME) indicates that gender plays a significant role to abate or magnify the negative effect of childhood poverty on adult labor market outcomes. The average annual labor income gap between women who were not experienced persistent childhood poverty and those who were is significantly larger than a similar comparison for men. On the other hand, the average hours worked and the number of weeks unemployed gaps between men who were not experienced persistent childhood poverty and those who were is significantly larger than a similar comparison for women.

Similar PSM estimation for effects of poverty on mediator outcome variables as well as ACME of poverty on labor market outcomes have been studied separately for the four stages of child development. They showed that childhood poverty during early childhood has the largest and most significant deterioration effect on overall childhood health capital and educational attainment. The proportion of individuals who had a healthy childhood is significantly lower (by 16.04 percent) for the group who experienced persistent poverty during their early childhood as compared to those who did not. Similarly, the proportion of individuals who have a college degree is significantly lower (by 11.19 percent) for those individuals who experience persistent poverty during early childhood. Hence, the early childhood stage is critical in terms of the long-run effects of poverty on health and educational attainment. Furthermore, for all stages of child development, except infancy, persistent childhood poverty significantly and negatively impacts adult hours worked.

The sensitivity analysis using ACME's sensitivity parameters and 125 percent of the federal poverty line reinforces the above results of both PSM and ACME estimations. From the findings and methods of estimations used to measure the effect of childhood poverty on mediator and adult outcomes, this study contributes twofold. First, due to the time lag between the cause (childhood poverty) and its effect (adult labor outcomes), this study focuses on health and education to play mediating roles. This estimation procedure enables us to decompose the total effect of childhood poverty on outcome variables into indirect effects through mediator variables (health and education) and direct effects. Second, a separate analysis of childhood poverty and its effect is conducted at four major stages of child development, which are infancy, early childhood, mid-childhood, and late childhood. Unlike the estimation procedure which treats the whole childhood years (birth to 18 years old) as a single period, the separate analyses enable us to identify critical stage of child development that affect adult outcomes the most.

The rest of this chapter is structured as follows: Section 2 reviews major literature. Section 3 presents the theoretical framework that relates childhood poverty to mediator variables (health and education) as well as labor market outcome variables (labor income, hours worked, and the number of weeks unemployed). Section 4 describes the methodology of the study: data, descriptive statistics, and identification strategy. Section 5 provides empirical results and sensitivity analyses that separately analyze the consistency of the effect of childhood poverty when the assumptions of ACME estimation are relaxed as well as the poverty line is redefined to 125 percent of the federal poverty line. Section 6 discusses the major findings and conclusions.

2 Theoretical Model

Parental investment is referred to as any expenditure (time, energy, resources, etc.) that parents incur to benefit an offspring (Wang, 2015). A growing body of research in economics and developmental psychology has argued that attributes shaped by a parental investment during childhood have a significant role in determining adult outcomes. At least 50 percent of the variability of lifetime earnings across individuals results from attributes of persons determined by age 18 (Keane & Wolpin, 1997; Cunha et al., 2005; Huggett et al., 2011). This implies that the financial well-being of parents, which is a major determinant for investment in children, has an effect on the human capital development of children and their adult outcomes.

Hence, poverty that occurs during childhood, when foundational cognitive and non-cognitive skills are being formed, is likely to have more severe and long-term consequences than poverty that occurs later. This assertion is in line with the argument which claims that human capital production is a cumulative process subject to critical investment periods (Cunha & Heckman, 2007; Kautz et al., 2014).

In this study, the human capital measures of a child not only embrace educational attainment but also accumulated health capital. Cunha and Heckman (2007) explained that although thousands of articles and books followed on human capital dimensions of education and training, there have been fewer discussions of health as human capital. However, health and education are considered to be the most critical components of human capital (Schultz, 1961; Grossman, 2000). Investing in them makes individuals more productive and there are several important differences between them as well (Galama & van Kippersluis, 2015). Hence, the theoretical framework focuses on how childhood poverty impacts the production of both children's health and educational attainment which in turn affects the accumulation of human capital and adult labor market outcomes.

The theoretical model used in this study follows Galama and van Kippersluis (2015) and Meghir, Nix, and Attanasio's (2015) procedure as they considered both health and education as components in the formation of human capital. In their terms, these two components of human capital are loosely referred to as "health capital" and "skill capital". This study also treats health as a form of human capital that is distinct from the component of human capital that is accumulated through education and training.

The theoretical framework focuses on a single agent who goes through two groups of time periods: childhood and adulthood. For the former, the child has no decision making role, whereas, in the latter period, the child becomes a decision-maker and makes an optimal decision based on a utility function. Hence, during the childhood period children's human capital (health and education capitals) are accumulated based on decisions made by parents at the household level.

Accumulated human capital at the beginning of adulthood (H) is mostly contributed by investment in a child's education (e) and health (h). Here, e is broadly defined to represent both cognitive and non-cognitive skills. Hence, human capital function is defined as:

$$H = H(e, h) \tag{1}$$

The cognitive and noncognitive development, as well as health capital accumulation from investment in education and health, are produced throughout childhood. The process is governed by production functions that define how parental investment determines children's skills and health capital.

$$e = G(I^e) \tag{2}$$

$$h = F(I^h) \tag{3}$$

where I^e and I^h are parental investments for the production of child education and health for the whole childhood period. In this segment of the theoretical framework, the childhood period (from birth up to age 18) is treated as a single period. Both functions are assumed to be strictly increasing and strictly concave. Parental investment in children's health takes place through expenditures on medical care and time investments (e.g., exercise). Parents invest in children's skill development through outlays for schooling and on-the-job training. In addition, parents also make time investments in children to teach them skills that are incorporated as part of human capital. However, the parents' time input analysis is not included in this study.

Skill capital e (equation 2) and health capital h (equation 3) can be improved through investments in skill capital (I^e) and health (I^h), respectively, that depend on parental labor and non-labor income. Parental income is defined as:

$$A = wN + y \tag{4}$$

where w is wage rate, N is hours worked and y is non-labor income.

Productions of skill and health capital, which use market goods and services as inputs, are functions of the household's intertemporal income. They are denoted by $X_e(A)$ and $X_h(A)$, respectively. In addition, parents' own time inputs for a child's skill and health capital improvement, τ_e and τ_h, are considered as components of the two types of investment in children. In this study, the time inputs are not empirically analyzed due to data limitations. The two types of investment can be expressed as:

$$I^e = I_e[X_e(A), \tau_e] \quad \text{and} \quad I^h = I_h[X_h(A), \tau_h]. \tag{5}$$

The skill-capital (e) and health-capital (h) production processes are assumed to be increasing and strictly concave with respect to the investment inputs. This concavity implies:

$$\begin{array}{cccccc} \frac{\partial e}{\partial X_e} & > & 0; & \frac{\partial^2 e}{\partial X_e^2} & < & 0; \\ \frac{\partial h}{\partial X_h} & > & 0; \quad \text{and} & \frac{\partial^2 h}{\partial X_h^2} & < & 0; \end{array}$$

This assumption of diminishing returns to investment (concavity) addresses the degeneracy of the solution for investment that plagues the health-capital literature as a result of the common assumption of constant returns to scale (Galama & Van Kippersluis, 2013; Galama, 2015).

Equations (1) through (5) show how parental investment decisions play a role in linking children's human capital accumulation with the household's income. This paves the way to show the relationship between childhood poverty and human capital development. Therefore, growing up in a household with a lower income (A) hampers human capital development through low investment in the children's education and health (I^h and I^h, respectively). Hence, the incidence of household poverty (lower A) has a deteriorating effect on children's health outcome i.e., there is a positive relationship between household income and children's health capital accumulation:

$$\frac{\partial h}{\partial A} = G_I^{'} \frac{\partial I^h}{\partial A} \quad > \quad 0 \tag{6}$$

Similarly, the negative effect of poverty incidence (lower A) on child educational outcome is thus given by:

$$\frac{\partial e}{\partial A} = F_I^{'} \frac{\partial I^e}{\partial A} \quad > \quad 0 \tag{7}$$

Consequently, accumulated human capital at the beginning of adulthood (H) is positively affected by households' income as:

$$\frac{\partial H}{\partial A} = \underbrace{H_e^{'}\frac{\partial e}{\partial A}}_{+} + \underbrace{H_h^{'}\frac{\partial h}{\partial A}}_{+} > 0 \tag{8}$$

which has an effect on the determination of labor market outcomes.

The early influential literature on children's human capital accumulation, for example, Becker and Tomes (1979; 1986) collapsed childhood into a single period and implicitly assumed that investment at all ages of the child is the perfect substitute. This is similar to the discussion made so far based on equation (1) through equation (8). This assumption misses an important feature of the skill development process since all stages of child development are not equally critical for acquiring specific types of skills. In this study, I assume that different stages of child development play a different role in the process of child human capital accumulation. Based on this assumption, a similar theoretical foundation for the relationship between parental income and children's human capital accumulation at different stages of child development is analyzed and presented as follows. Investments in health and education at different stages of child development are treated separately.

$$e = G(I_2^e, I_3^e, I_4^e) \tag{9}$$

$$h = F(I_1^h, I_2^h, I_3^h, I_4^h) \tag{10}$$

where subscripts 1, 2, 3, and 4 indicate infancy, early childhood, mid childhood and late childhood stages of child development. The parental income at each stage of child development is positively related to both health and education capital accumulation.

$$\frac{\partial h}{\partial A} = \frac{\partial G(.)}{\partial I_1^h}\frac{\partial I_1^h}{\partial A} + \frac{\partial G(.)}{\partial I_2^h}\frac{\partial I_2^h}{\partial A} + \frac{\partial G(.)}{\partial I_3^h}\frac{\partial I_3^h}{\partial A} + \frac{\partial G(.)}{\partial I_4^h}\frac{\partial I_4^h}{\partial A} > 0 \tag{11}$$

$\frac{\partial G(.)}{\partial I_1^h}$, $\frac{\partial G(.)}{\partial I_2^h}$, $\frac{\partial G(.)}{\partial I_3^h}$ and $\frac{\partial G(.)}{\partial I_4^h}$ are positive because of the strictly increasing and strictly concave assumptions. If $\frac{\partial G(.)}{\partial I_t^h} > \frac{\partial G(.)}{\partial I_{t'}^h}$ for all $t' \neq t$, t is a sensitive period. A sensitive period exists when the investment has a higher payoff in that period than in any of the others (but the payoff in other periods is not necessarily zero). For example Conti and Heckman (2012) showed that learning a second language is easier before age 12.

Similarly, the negative effect of poverty incidence (lower A) on child educational outcome for the three stages of child development that exclude infancy is thus given below. The infancy stage of child development is excluded while measuring parental income effect on investment in education.

$$\frac{\partial e}{\partial A} = \frac{\partial F(.)}{\partial I_2^h}\frac{\partial I_2^e}{\partial A} + \frac{\partial F(.)}{\partial I_3^h}\frac{\partial I_3^e}{\partial A} + \frac{\partial F(.)}{\partial I_4^h}\frac{\partial I_4^e}{\partial A} > 0 \tag{12}$$

Consequently, accumulated human capital at the beginning of adulthood (H) is positively affected by household income as:

$$\frac{\partial H}{\partial A} = \underbrace{H_e^{'}\frac{\partial e}{\partial A}}_{+} + \underbrace{H_h^{'}\frac{\partial h}{\partial A}}_{+} > 0 \tag{13}$$

The framework that shows the effect of childhood poverty on human capital accumulation during childhood in its entirety (equation 8) or at different stages of child development (equation 13) enables us to link childhood poverty and labor market outcomes as discussed in the next section.

Therefore, the effect of childhood poverty on each mediator outcome variable, health and educational capital, is stated in the following two hypotheses, which are derived from the above four equations (6, 7, 11, and 12).

Hypothesis 1: Other things remaining constant, childhood poverty reduces available resources allotted to purchase goods and services which are necessary to make an investment in child health. Hence, childhood poverty deteriorates the health capital of a child.

Hypothesis 2: Similarly, the incidence of childhood poverty reduces the educational capital of a child, *ceteris paribus*.

In the second (adulthood) period, children join the labor market and they start making their own labor supply decision. Hokayem and Ziliak's (2014) life cycle labor supply framework is employed to trace the effects of a child's cumulative capital of health and education on labor supply decisions. This step enables us to link optimal labor supply decision with the previous section analysis to determine the effect of childhood poverty on labor market outcomes that passes through the intermediaries, health and educational capitals.

The labor supply decision is a result of an agent's lifetime utility maximization process. The total income of the agent comprises non-labor income (y^c) and labor earnings (wN), where w is the before-tax wage rate. The superscript c in the non-labor income of children is added to differentiate it from parents' non-labor income. Income can be spent on nonmedical and medical consumption with a normalized price of 1. The resulting budget constraint is:

$$C = wN + y^c. \tag{14}$$

Following Shaw's (1989) specification, I defined the observed wage (w) as the product of adult human capital stock as expressed in equation (1), and rental rate on human capital (R), $w = R * H(e, h)$, where e is a composite function of investment in child education. The investment in child education depends on goods and services purchased from the market using parents' intertemporal income, stock of health and educational capital, and parental background. h is also a composite function defined as similar to e. The human capital that continues to accumulate during adulthood is an extension of human capital development during childhood. The rental rate, R, is the market price for the services of a unit of human capital. It is a positive market-clearing price at which the aggregate supply and aggregate demand for human capital services are in equilibrium. Hence, the wage rate is a function of accumulated human capital which is determined by parents' intertemporal income during childhood and a person's labor market decisions during adulthood.

The individual's endowment of time at each period is normalized to 1. Since I denoted N as the amount of labor it supplies, leisure becomes $1 - N$. It is also assumed that leisure is an argument in the utility function, more leisure leading to more utility or work has a disutility effect on an individual's welfare.

An individual chooses leisure time $(1 - N)$ and consumption (C) to maximize utility defined over leisure (L) and consumption(C), $U(L, C)$. Hence, the utility maximization problem is:

$$\begin{aligned} \underbrace{Max}_{L,C} \quad & U(L,C) \\ S.t. \quad & C = wN + y^c \end{aligned} \tag{15}$$

The maximum level of utility for the agent is attained if both the decision variables, L and C are optimally allocated.

The process of finding optimal values of the decision variables is presented as follows. The Lagrangian of equation (15) is written as:

$$\begin{aligned} \underbrace{Max}_{L,C} \quad L &= U(L,C) - \lambda[C - wN - y^c] \\ &= U(L,C) - \lambda[C - w(1-L) - y^c] \end{aligned} \tag{16}$$

Then, the first-order conditions are:

$$\frac{\partial L}{\partial L} = 0 \iff U_L - \lambda w = 0 \tag{17}$$

$$\frac{\partial L}{\partial C} = 0 \iff U_C - \lambda = 0 \tag{18}$$

$$\frac{\partial L}{\partial \lambda} = 0 \iff C = wN + y^c \tag{19}$$

Where

$$\begin{aligned} U_L &\equiv \tfrac{\partial U(L,C)}{\partial L} \\ U_C &\equiv \tfrac{\partial U(L,C)}{\partial C} \end{aligned}$$

Plugging the expression from equation (18) into equation (17) gives us:

$$U_L - wU_C = 0 \tag{20}$$

The first-order equation for leisure has been rewritten to more readily examine the effect of human capital investment on the optimal labor-leisure choice. To analyze this effect, decompose condition (20) into two parts:

1. U_L, which denotes the gain in current utility due to an increase in the number of leisure hours.

2. $-wU_C$, which is the utility loss due to a decrease in consumption that arises from a decrease in earnings. It is because leisure trades off hours worked.

The condition in equation (20), $U_L = wU_C$, is the traditional optimal condition wherein agents choose the optimal combination of consumption and leisure time which sets the ratio of the marginal substitution between consumption and leisure equal to relative prices at each time period.

The optimal decision explained above can be linked to the incidence of childhood poverty through human capital formation. From equations (8) and (13) together with Shaw's (1989) wage equation, the incidence of childhood poverty reduces human capital stock and consequently the wage rate. The reduction of the wage rate makes the slope of the budget line flatter than the original. This leads to a low level of labor supply (higher level of leisure) decision. On the other hand, higher household intertemporal income improves human capital stock and wage rate. The slope of the budget line becomes steeper and that leads to larger hours worked (low level of leisure).

Hence, the effect of the incidence of childhood poverty on adult labor outcomes can be expressed as follows:
Other things remaining constant, the incidence of childhood poverty deteriorates human capital stock (equations 8 and 13), which in effect decreases the wage rate of an individual. This is derived from the presumption that higher income leads to better health and better education. Better health and education in turn contribute positively to human capital accumulation ($H = H(e, h)$) that enhances wage rate; i.e.,

$$\frac{\partial w}{\partial A} = \underbrace{\frac{\partial w}{\partial H(.)}}_{+} \quad \underbrace{\frac{\partial H(.)}{\partial A}}_{+} \quad > \quad 0.$$

Hypothesis 3: Childhood poverty negatively affects hours worked through channels of human capital development and wage rate, *ceteris paribus*, for lower income individuals; i.e.,

$$\frac{\partial N}{\partial A} = \underbrace{\frac{\partial N}{\partial w}}_{(+)(-)(0)} \quad \underbrace{\frac{\partial w_t}{\partial H(.)}}_{+} \quad \underbrace{\frac{\partial H(.)}{\partial A}}_{+} \quad \gtreqless \quad 0.$$

An increase in w has opposite signed income and substitution effects whereas the net effect on hours worked is ambiguous. However, for lower income individuals, substitution effect is larger than income effect that leads to positive effect of wage rate on hours worked. In this case, childhood poverty negatively affect hours worked during adulthood.

Hypothesis 4: Childhood poverty has a negative effect on labor earnings (E) through both wage rate and hours worked, *ceteris paribus*. This hypothesis emanates from the hypothesized relationship established for incidence of childhood poverty with both wage rate and hours worked as:

$$\frac{\partial E}{\partial A} = \frac{\partial wN}{\partial A} = w \underbrace{\frac{\partial N}{\partial A}}_{+} + N \underbrace{\frac{\partial w}{\partial A}}_{+} > 0.$$

3 Data and Descriptive Statistics

The PSID began interviewing a national probability sample of families in 1968 to assess President Lyndon Johnson's war on poverty. The original 1968 PSID sample was drawn from two independent samples: an over-sample of 1,872 low-income families from the Survey of Economic Opportunity (the "SEO sample") and a nationally representative sample of 2,930 families designed by the Survey Research Center at the University of Michigan (the "SRC sample"). The oversampling of families who were poor in the late 1960s resulted in a sizable subsample of African Americans. These two samples combined to constitute a national probability sample of U.S. families in 1968 (Institute for Social Research, University of Michigan, 2019). These families were re-interviewed each year through 1997 when interviewing became biennial. All persons in PSID families in 1968 are followed in subsequent waves. In addition, anyone born to or adopted by PSID sample members is also followed. When children become adults and leave their parents' homes, they become their own PSID family unit and are interviewed in each wave (Johnson & Schoeni, 2011). This method of sampling "split offs" has been found an important procedure for yielding a nationally representative sample (Fitzgerald et al., 1998).

The latest PSID data has 41 panel waves from 1968 to 2019 and has a total of 82,576 individuals. This study relies on extracted data that has both childhood and adult labor market outcome information for the same individual. Specifically, I chose PSID sample members born in 1968 and later in order to have full information about their childhood experience and adult outcomes. However, the inclusion of all individuals with ranges of adult years is not appropriate since the annual labor income of an agent fluctuates for different stages of one's life cycle. Instead, I limited the sample to the observation of adults who were born in 1968 or later and with the age ranges of 35 to 54 years old. This age range was chosen based on the U.S. Bureau of Labor Statistics (2020) data, which indicates the stated age range is a plateau of annual labor income. Typically, prior to age 35 average labor incomes are rising and after age 54 labor incomes are declining.

Hence, the data used in this study comprises both childhood and adult covariates. For childhood years, I included children's information together with parents' background information to measure childhood poverty status. The covariates here include household income, family size, number of adults in the household, race, parental education, parents' age when the child was born, children's education, children's health status, and parental marital status. In addition, the labor market information and other covariates of the same individuals when they became adults are extracted. These covariates include education, health status, income from the labor market, hours worked and the number of weeks unemployed per year. This allows us to link individuals' childhood experiences with their adult labor market outcomes. Limiting the sample as explained above yields 2,503 individuals of whom 52.06 percent (1,303) are female. The sample's decomposition in terms of race indicates that 67.76 percent of respondents are White, 30.84 percent are Black and 1.40 percent are of other races. Because the average values of labor market outcome variables are considered across different waves, the number of observations and number of individuals are the same.

In the PSID data, in each interview year, family annual income is collected for the prior calendar year. This data in combination with the family size is used to construct the poverty status of each household in which the sampled children were living. Then, the poverty status of the household is analyzed based on the official definition of poverty. Under the official definition, a family is poor if its gross annual money income is below the US federal poverty level. The strength of using this official poverty measure is that it allows for straightforward poverty status comparisons over time among households. I used weighted average poverty thresholds provided by the U.S. Bureau of the Census and combined it with family annual income and family size data of the PSID to compute household poverty status. For example, in 1975, the federal poverty threshold for a family of three was $4,293. Since the household poverty analysis is directly cascaded to childhood poverty analysis, a child who lives in a household that earns less than $4,293 and has a family size of three or more is considered as a poor child.

The childhood poverty analysis is done for the whole childhood age range and for the four stages of child development separately. For both types of descriptive analyses, three types of livelihood status of a child, viz., persistently poor, ever poor, and never poor, are identified. A persistently poor child lived in a poor family for at least half of his or her childhood years. The ever-poor livelihood status indicates that a child lived in a poor household for at least one year during his or her childhood years but is not persistently poor. The never-poor livelihood status indicates that a child lived in a household that never experienced poverty during his or her childhood years. Similar criteria were employed to categorize the livelihood status of children in the four stages of child development. For example, a child is considered persistently poor during early childhood if he or she lived in a poor household for half or more of his or her early childhood years. Similarly, a child is considered ever poor during early childhood years if he or she lived at least one year in poverty but is not persistently poor. A similar categorization applies to the other stages of child development.

Following children from birth through age 18 reveals that 13.9 percent of children are persistently poor, meaning that they spent at least half their childhood years in a household that earns an income below the federal poverty threshold. As Table 1 shows, from the remaining proportion 24.73 percent of the children experienced poverty at least one year during their childhood and the remaining 61.37 percent never experience poverty during their childhood. This figure is not similar across different races. Children of color face much worse than average. While 30.57 percent of Black children were persistently poor, only 6.1 percent of White children and 20 percent of other children were persistently poor. The proportion of children who never experienced poverty is largest for White children and smallest for Black children.

Table 1: Percentage of Childhood Poverty

	Persistently Poor	Ever Poor	Never Experienced Poverty
White	6.1	22.46	71.34
Black	30.57	29.53	39.90
Others	20.00	28.57	51.43
Total	**13.90**	**24.73**	**61.37**

Notes: Persistently poor children are poor at least half the years from birth through age 18. "Others" includes Hispanic, Asian American and Pacific Islander, and Native American children. I am unable to separately examine these groups because of sample size limitations.

Since experiencing poverty at different stages of child development has different effects, decomposition of childhood poverty across stages of a child's development is important. During the infancy period, 152 (6.07 percent) of children were persistently poor. This figure too is not evenly distributed among different racial groups. 14.64 percent of Black children are persistently poor whereas the same figure for White children is 2.3 percent. Out of the total individuals who had experienced persistent poverty during their infancy stage, 102 (67 percent) of them had experienced persistent poverty in their entire childhood.

During their early childhood, 418 (16.70 percent) of the children were persistently poor. Similar figures during their mid-childhood and late childhood are 387 (15.46 percent) and 499 (19.94 percent), respectively. This decomposed analysis also reveals unevenly distributed economic well-being of children of different races as shown in Table 2. Out of the total individuals who had experienced persistent poverty during their early childhood period, 286

(68.4 percent) of them had experienced persistent poverty in their entire childhood. The similar figure for mid-childhood and late childhood stages of child development are 317 (81.9 percent) and 300 (60.12 percent), respectively.

Table 2: Childhood Poverty at Different Stages of Child Development

		Persistently Poor	Ever Poor	Never Poor
Infancy	**White**	2.30	7.02	90.68
	Black	14.64	18.91	66.45
	Others	0	11.43	88.57
	Total	**6.07**	**10.75**	**83.18**
Early Childhood	**White**	8.73	7.13	84.14
	Black	34.59	12.82	52.59
	Others	8.57	25.71	65.71
	Total	**16.70**	**9.15**	**74.15**
Mid Childhood	**White**	7.43	12.74	79.83
	Black	32.64	19.30	48.06
	Others	25.71	17.14	57.14
	Total	**15.46**	**14.82**	**69.72**
Late Childhood	**White**	11.20	13.27	75.53
	Black	38.86	15.80	45.34
	Others	25.71	11.43	62.86
	Total	**19.94**	**14.02**	**66.04**

Table 3 presents definitions of all analytical variables used. The variables are extracted from the PSID survey research center data set. The data provides information about individual characteristics: race, age, gender, and childhood health condition. The second group of variables provides information about parental characteristics: parents' educational level, their age when the respondents were born, mothers' marital status while raising the children, their tenancy status, and the streams of the family income that helps to determine the childhood poverty status of respondents. Furthermore, the third group of variables includes major dependent variables of labor market outcomes together with health and education-related mediator outcomes. The labor market outcome variables are labor income, hours worked, and the number of weeks unemployed in a year.

Table 3: Definitions of Major Variables

Variable	Definition
Persistently poor	=1 if the respondent experienced childhood poverty for 9 years or more, 0 otherwise
Mother's age	Age of mother at birth
Father's age	Age of father when the child was born
Mother HS graduate	=1 if the mother has completed high school, 0 otherwise
Father HS graduate	=1 if the father has completed high school, 0 otherwise
Mother college	=1 if the mother has at least one year of college education, 0 otherwise
Father college	=1 if the father has at least one year of college education, 0 otherwise
Mother dropout	=1 if the mother has not completed high school, 0 otherwise
Father dropout	=1 if the father has not completed high school, 0 otherwise
Single mother	=1 if the respondent is raised by single mother, 0 otherwise
Tenancy	=1 if parents own their own house, 0 otherwise
Family size	Respondent's family size when she or he was a child
Number of Adults	Number of adults in the family
Male	=1 if the respondent is male, 0 if the respondent is female.
Healthy childhood	=1 if the respondent has reported an excellent or very good or good childhood health status, 0 otherwise
White	=1 if the respondent is White, 0 otherwise.
Black	=1 if the respondent is Black, 0 otherwise
Other	=1 if the respondent is other than White or Black, 0 otherwise
Years of schooling	Respondent's number of years of schooling
School dropouts	=1 if the respondent has not completed high school, 0 otherwise
Highschool graduate	=1 if the respondent has completed high school, 0 otherwise
College	=1 if the respondent has completed college education, 0 otherwise.
Average labor income	Respondent's average labor income per annum
Average hours worked	Respondent's average worked hours per annum
Average unemployment weeks	Respondent's average number of weeks stayed unemployed per annum

In the PSID data, one of the mediator variables, education, is measured by years of schooling. They take values ranging from 0 (no schooling) to 17, where 12 indicates that an individual has completed high school, 16 indicates that an individual has completed a college degree, and 17 indicating that the individual has done some postgraduate work (beyond college). The data is designed such that the years of schooling are the same as the number of years necessary to complete a certain level of education. For instance, if students are taking 5 or even 6 years to complete study at college, their years of schooling are still reported as 16.

The average annual values of labor market variables (labor income, hours worked, number of weeks unemployed) are manipulated by taking the average of the annual values when the individual is in the age range between 35 to 54 years old. In addition, the variable expressed in monetary terms, labor income, is adjusted for inflation using the conversion rate from the consumer price index (CPI) of the U.S. Bureau of Labor Statistics (2020). Table 4 presents the average value and standard deviations of major variables for respondents in the study sample together with the corresponding minimum and maximum values.

Table 4: Summary Statistics of Major Variables

	Mean	**SD**	**Min**	**Max**	**N**
Persistently poor	0.139	0.346	0	1	2503
Mother's age	26.452	7.06	12	69	2503
Father's age	29.05	8.046	15	81	2503
Mother HS graduate	0.312	0.463	0	1	2503
Father HS graduate	0.286	0.452	0	1	2503
Mother college	0.491	0.500	0	1	2503
Father college	0.467	0.499	0	1	2503
Mother dropout	0.036	0.186	0	1	2503
Father dropout	0.067	0.25	0	1	2503
Single mother	0.17	0.377	0	1	2503
Tenancy status	0.618	0.486	0	1	2503
Family size	4.454	1.265	2	11	2503
Number of Adult	2.083	0.458	1	6	2503
Male	0.479	0.480	0	1	2503
Healthy childhood	0.469	0.499	0	1	2503
White	0.678	0.467	0	1	2503
Black	0.308	0.462	0	1	2503
Other	0.014	0. 117	0	1	2503
Years of schooling	14.886	1.939	8	17	2503
School dropouts	0.022	0.145	0	1	2503
Highschool graduate	0.479	0.500	0	1	2503
College	0.500	0.500	0	1	2503
Average labor income	63,650.68	93,636.35	20	1,876,069	2503
Average hours worked	1,982.352	645.424	7	5,460	2503
Average unemployment weeks	2.051	5.734	0	52	2503

Table 5 describes the comparison of the mean values of the major variables based on the childhood poverty status of individuals. Parental characteristics comparisons showed that those who grew up poor performed lower in better well-being indicator variables like educational achievement and tenancy status. More than 50 percent of parents of individuals who grew up non-poor did have at least one year of a college education. However, only 23.6 percent of mothers and 19.5 percent of fathers of individuals who grew up poor did have at least one year of a college education. The group also performs lower from the perspectives of childhood health status, college education, dropout rate, and adult labor market outcomes.

Table 5: **Test on Major Variables Means' Difference by Poverty Status**

Variable	Non-Poor	Poor	Difference	T-stat
Mother's age	26.239	27.770	-1.531***	(-3.76)
Father's age	28.794	30.647	-1.853***	(-4.00)
Mother HS graduate	0.305	0.356	-0.051*	(-1.92)
Father HS graduate	0.278	0.336	-0.058**	(-2.23)
Mother college	0.532	0.236	0.297***	(10.49)
Father college	0.511	0.195	0.316***	(11.23)
Mother dropout	0.032	0.060	-0.028***	(-2.64)
Father dropout	0.062	0.098	-0.036**	(-2.50)
Single mother	0.136	0.388	-0.252***	(-11.90)
Tenancy status	0.671	0.290	0.381***	(14.11)
Family size	4.316	5.310	-0.995***	(-14.14)
Number of Adult	2.075	2.133	-0.0584**	(-2.21)
Male	0.496	0.376	0.120***	(4.16)
Healthy childhood	0.504	0.252	0.252***	(8.86)
White	0.738	0.301	0.437***	(17.08)
Black	0.249	0.678	-0.429***	(-16.99)
Others	0.032	0.033	-0.007	(-1.05)
Years of schooling	15.107	13.520	1.587***	(14.77)
College	0.548	0.204	0.344***	(12.24)
High school graduate	0.438	0.733	-0.295***	(-10.44)
School dropouts	0.015	0.063	-0.0484***	(-5.80)
Average labor income	67,743.860	38,303.570	29,440.3***	(5.47)
Average hours worked	2,005.156	1,841.138	164.0***	(4.41)
Average unemployment weeks	1.649	4.602	-2.953***	(-8.43)
N	2,155	348		

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Empirical Model

This section explains two identification methods that estimate the effect of childhood poverty on both mediator and labor market outcomes. The first method uses propensity scores to estimate the propensity of a child to be raised in a poor household and the effect on mediator outcomes (child's health and education), which is equivalent to the average treatment effect on the treated. The second method is the average causal mediation effect which deals with the total effect of childhood poverty on labor market outcomes (hours worked, labor income, and the number of weeks unemployed) and decomposes the indirect effect that comes through mediator outcomes (educational achievement and health production during childhood).

4.1 Identification

There is some sort of consensus in the literature that growing up in a poor family is associated with a higher tendency of falling below the poverty threshold in adulthood. However, the key contentious question for policy is whether this association is truly causal in the sense that poverty in childhood per se influences adult outcomes or whether it is driven by other factors that are correlated with both childhood poverty and those outcomes. Moreover, it is relevant for policy makers to examine plausible causal channels through which growing up in a poor household affects the individual's economic and social status as an adult.

Because of the complexity of the transmission mechanism that links childhood poverty with adult labor market outcomes (hours worked, labor income, and the number of weeks unemployed), meticulously designed statistical techniques are needed to trace the long-run effect of child poverty on adult outcomes. Mediator causal analysis plays this role, as it allows inter-linkage among initial causes, intermediaries, and final outcomes. It is employed as a framework to quantify the effect of experiencing financial difficulties during childhood on adult labor market outcomes. The framework also introduces individuals' educational capital and childhood health covariates as mediator variables. The following subsection discusses a framework employed to analyze the impact of childhood poverty on mediator variables, followed by the main empirical method of analysis that gauges causal mediation effect of childhood poverty on major outcome variables.

4.1.1 Average Treatment Effect on the Treated

The potential outcomes approach for causal inference follows a framework from Robin (1974, 1978). Consider a set of n individuals with subscript i: $i = 1, 2, .., n$. The treatment in this study is whether the child was growing up in a poor household or not, $T_i = 1$ (treated or growing up in a poor household) and $T_i = 0$ (control or growing up in a non-poor household).

The treated and non-treated groups are identified using the combination of the PSID survey data and annual poverty-line data from the U.S. Bureau of the Census. A child who lived in poverty for more than half of his or her childhood ages (i.e., 9 or more years) is considered as a persistently poor child. The group consisting of these persistently poor children is considered as a treated group. The other groups are included in the control group. Similar definitions are considered to analyze the impacts of childhood poverty at different stages of child development. The treated group consists of individuals who spent half or more years of the specific stages of child development in poverty. The rest are the control group.

For each individual i, we observe a vector of pre-treatment covariates, X_i and vector of outcome variables (childhood health status and educational attainment) associated with the treatment and they are denoted by $Y_i(1)$ for being a poor child and $Y_i(0)$ for not being a poor child. Then, the average treatment on the treated (ATT) is defined as:

$$
\begin{aligned}
ATT(X) &= E[Y_i(1) - Y_i(0)|T_i = 1] \\
&= E_{X_i|T_i=1}[E[Y_i(1) - Y_i(0)|T_i = 1, X_i]] \\
&= E_{X_i|T_i=1}[E[Y_i(1)|T_i = 1, X_i]] - E_{X_i|T_i=1}[E[Y_i(0)|T_i = 1, X_i]]
\end{aligned}
\tag{21}
$$

The second term of the last equation, which indicates the outcome of the treated individual if she or he would not be treated, is not observable but represented by the counterfactual.

The outcome variables are childhood health status derived from an individual's report about her or his childhood health. A healthy childhood dummy variable is created with a value of 1 for those who reported that they had good, very good, and excellent status of childhood health and 0 for the rest. The other outcome variable is the educational attainment extracted from the years of schooling variable of an individual.

The pre-treatment confounders are mother's age at birth, father's age when the child was born, educational status of the mother (dummy variables of school dropouts, high school completed, and at least one year of college education), educational status of the father, whether the child is raised by a single mother or not, homeownership status of the household, family size, number of adults in the family and race. These covariates affect the income-generating and asset-building capacity of a household, then in effect determine households' potential to invest in the production of a child's health and education. The treatment variable, childhood poverty, is endogeneous before matching since it is not independent of these factors, which can affect the outcome variables (child health and educational attainment).

The central assumption of the propensity score matching is unconfoundedness. The "assignment to treatment" is unconfounded given the set of observable pre-treatment characteristics: $Y_i(0) \perp T_i | X_i$, where, within each cell defined by X, the treatment assignment is random and the outcome of controls is used to estimate counterfactual outcome of the treated in case of no treatment. Let $p(X)$ be the probability of growing up in a poor household given the set of covariates $X : p(X) = Pr(T = 1|X = x) = E[T|X = x]$. Rosenbaum and Rubin (1983) showed that, if the potential outcome $Y_i(0)$ is independent of treatment assignment conditional on X, it is also independent of treatment conditional on $p(X)$: $Y_i(0) \perp Ti | p(X_i)$. Thus, for a given propensity score value, exposure to treatment can be considered as random and thus poor and non-poor children should be observationally equivalent on average. This is also checked by pstest that evaluates balance among covariates after the propensity score matching.

Formally, given the population of units i, if we know the propensity score $p(X_i)$, the average effect of being poor on those exposed to childhood poverty (the average treatment effect on treated [ATT]) can be rewritten as:

$$\begin{aligned}\tau &= E[Y_i(1) - Y_i(0)|T_i = 1] \\ &= E_{p(X_i)|T_i=1}[E[Y_i(1) - Y_i(0)|T_i = 1, p(X_i)]] \\ &= E_{p(X_i)|T_i=1}[E[Y_i(1)|T_i = 1, p(X_i)]] - E_{p(X_i)|T_i=1}[E[Y_i(0)|T_i = 1, p(X_i)]]\end{aligned} \tag{22}$$

When $T_i = 1$, then $Y_i(1) = Y_i$, whereas $Y_i(0)$ is never observed.

To estimate the ATT, the first step is to estimate the propensity score of growing up poor using a probit model, $\hat{p}(X_i)$; then the unobserved potential outcomes are estimated based on the propensity score (PS) matching. The propensity score matching technique has been chosen for this study because of the following advantages. Guo et al. (2020) argued that the greatest advantage of the propensity score is its reduction in dimensions, which solves the problem of insufficient sample cases in exact matching. Second, matching does not require functional form assumptions for the relationship between the expected outcomes and the values of characteristics; i.e., the relationship is left unspecified and can have a quite general form (Bryson et al., 2002).

The nearest neighbor matching technique with replacement and caliper of 0.001 is employed for the above procedure. Let l denote the index of the unit in the opposite treatment group that is closest to unit i :

$$|\hat{p}(X_l) - \hat{p}(X_i)| \leq |\hat{p}(X_j) - \hat{p}(X_i)| \qquad \forall j, T_j \neq T_i \tag{23}$$

This procedure enables us to select a control group from non-treated individuals (in this case non-poor as a child) who are very similar to treated individuals in terms of their probability of being poor during their childhood. Then the average treatment effect on treated estimate τ is estimated by $\hat{\tau} = 1/n_1 \sum_{n=1}^{n_1}[\hat{Y}_i(1) - \hat{Y}_i(0)]$ with $\hat{Y}_i(0) = Y_l(0), \hat{Y}_i(1) = Y_i$ and n_1 is the number of individuals who grew up poor. These estimates of the average treatment effect on the treated enable us to test the first two hypotheses discussed under the theoretical model.

A similar propensity score matching estimation procedure is employed for the four stages of child development. The treated groups comprise individuals who lived half or more years of their life of that particular stage in poverty. The rest were considered as the control group. The mediator outcome variables and the pre-treatment covariates are the same for infancy stages of child development. But, the other stages of child development incorporate the poverty statuses of the previous stages as part of the pre-treatment covariates.

The discussion we made so far enables us to measure the effect of childhood poverty on mediator variables. However, its effect transcends to labor market outcomes through its effect on mediator outcomes (health and education) and other channels. The next section deals with the estimation method, which quantifies the total effect of childhood poverty on labor market outcomes and its decomposition into direct effect and indirect effect which passes through the mediator outcomes.

4.1.2 Average Causal Mediation Effect

Hypothetical interventions that improve or deteriorate the health capital and/or educational attainment of an individual can affect adult outcomes. Childhood poverty is one of these types of shocks that deteriorate the health and educational capital of a person and consequently affect labor market outcomes. In addition to measuring the total impact of childhood poverty on mediator outcomes using the method explained in the previous section, in this study we aim to decompose the causal effect of childhood poverty on adult earnings, hours worked, and the number of weeks unemployed into an indirect effect, transmitted through health status and educational attainment, and a direct effect (which includes all other potential mechanisms).

This study follows a framework developed by Imai and Yamamoto (2013) to estimate the total effect and its decomposition. Unlike prior literature on the topic, their method considers a possible causal relationship between mediator variables. In this study I assumed that child health affects educational achievement and the assumption is in line with Gracy et al.'s (2017) findings. Poor children have more prevalence of asthma, vision problems, hearing loss, dental pain, and persistent hunger which cause absenteeism and lack of concentration while attending school. These negative health conditions in turn lead to negative school outcomes. The negative educational outcomes are manifested in the form of grade repetition, lower academic scores, disengagement with school, and attendance problems.

The reason for the unidirectional effect between health and education is because parents' investment decisions on child health influence a child's health outcome that can also affect the child's educational performance. However, since children are not decision-makers in the household, their educational attainment cannot influence the health investment decision of the household and the child's health outcome. Figure 2 depicts the interaction between the two mediator variables (H and E) together with the childhood poverty (treatment (T)) and outcome variables (Y). In both panels, the treatment variable T could affect the outcome Y in three ways: through the main mediator of interest E, through the set of alternative mediator H, and directly.

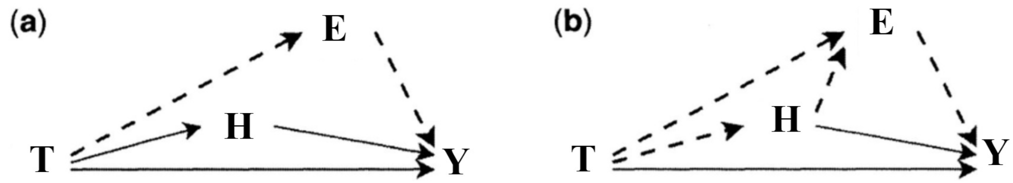

Figure 2: Treatment, mediators and outcomes (adapted from Imai and Yamamoto, 2013)

In this study, the interaction among the variables is similar to the one depicted in Panel (b), where T (childhood poverty) affects outcome Y (labor income, hours worked and the number of weeks unemployed), mediators E (educational attainment) and H (childhood health status). The mediator H confounds the relationship between the mediator of interest E and the outcome Y. Panel (a) is not considered in this study since it implicitly assumes the absence of a causal relationship between the corresponding mediators. Unlike Panel (a), for which Imai and Yamamoto (2013) developed a different methodology, Panel (b) is an alternative scenario, where H can affect Y either directly or indirectly through E, thereby allowing for the potential causal relationship between E and H. The quantity of interest for the proposed method is the average causal mediation effect among the treated (ACMET) with respect to E, which is represented by the dashed arrows connecting T and Y through E.

The Setup and Assumptions

The potential values of educational attainment (E) is affected by health status of a child as explained above. That is, $E_i(t, h)$ denotes the potential value of educational attainment for unit i when the childhood poverty status is $t = 0, 1$, and the alternative mediator H (childhood health status) takes the value of $h = 0, 1$. Then, the observed value of the mediator for this unit is given by $E_i = E_i(T_i, H_i(T_i))$. Similarly, $Y_i(t, E(H(t)))$ denotes the potential outcome under the treatment status t and the mediator value e derived from h value of H, where the observed outcome Y_i equals $Y_i = (T_i, E_i(T_i, H_i(T_i)))$.

Under this setting, for each unit, the causal mediation (with respect to E) and direct effects are defined as:

$$\delta_i(t) \equiv Y_i(t, E_i(1, H_i(1)), H_i(t)) - Y_i(t, E_i(0, H_i(0)), H_i(t)) \tag{24}$$

$$\zeta_i(t) \equiv Y_i(1, E_i(t, H_i(t)), H_i(1)) - Y_i(0, E_i(t, H_i(t)), H_i(0)) \tag{25}$$

For $t = 0, 1$, where $\delta_i(t)$ corresponds to the causal effect of childhood poverty on the labor market outcomes that transmits through the mediator of interest (educational attainment). Thus, for annual labor income, $\delta_i(t)$ represents the difference between the two potential labor incomes for subject i, who actually receives the treatment (persistently poor during childhood) and those who are in the control group (non-poor during childhood). This is a causal mediation effect or indirect effect of education, which is affected by childhood poverty and health status, on annual labor income. The indirect effect on the other labor market outcomes, hours worked and the number of weeks unemployed can also be explained in a similar fashion.

On the other hand, $\zeta_i(t)$ represents the rest of childhood poverty effect (denoted by the solid arrow at the bottom of Panel (b) in Figure 2 and the combination of the arrows that go from T to Y through H but not through E). Hence, $\zeta_i(1) \equiv Y_i(1, E_i(1, H_i(1)), H_i(1)) - Y_i(0, E_i(1, H_i(1)), H_i(0))$ represents the difference in annual labor income under treatment (the individual who experienced persistent childhood poverty) and control (who did not experience persistent childhood poverty), holding the level of education constant at the level that would be realized under treatment.

Thus, as expected, the sum of these two effects equals the total treatment effect,

$$\tau_i \equiv Y_i(1, E_i(1, H_i(1)), H_i(1)) - Y_i(0, E_i(0, H_i(0)), H_i(0)) \tag{26}$$

$$\tau_i = \delta_i(t) + \zeta_i(1-t) \qquad for \quad t = 0, 1 \tag{27}$$

Instead of the individual-level effects which are discussed so far, we are interested in estimating average effects, i.e., average causal mediation effect (ACME) or $\bar{\delta}_i(t) \equiv E(\delta_i(t))$, average direct effect or $\bar{\zeta}_i(t) \equiv E(\zeta_i(t))$ and average total effects or $\bar{\tau} \equiv E(\tau_i)$.

The following weaker version of the sequential ignorability (SI) and interaction of treatment and mediator assumptions are needed in order to identify ACME under the scenario depicted in panel (b) of Figure 2 .

Assumption 1: Sequential Ignorability with Multiple Causally Dependent Mediators

The following three conditional independence statements are assumed:

$$\begin{aligned}
&Y_i(t, e, h), E_i(t, h), H_i(t) \perp T_i | X_i = x \\
&Y_i(t, e, h), E_i(t, h) \perp H_i | T_i = t, X_i = x \\
&Y_i(t, e, h) \perp E_i | H_i(t) = h, T_i = t, X_i = x \quad \text{for any} \quad t, e, h, x.
\end{aligned} \tag{28}$$

Sequential ignorability implies that the treatment assignment is essentially random after adjusting for observed pre-treatment covariates and the assignment of mediator values is also essentially random once both observed treatment and the same set of observed pre-treatment covariates are adjusted for (Imai et al., 2011, pp. 863–864).

Factors that determine parents' income-generating ability and factors that determine the per capita share of household members from the total income are considered as the pre-treatment confounders. Hence, treatment (childhood poverty) is assumed to be random or ignorable given the confounders that include mother's age at birth, father's age when the child was born, educational status of mother (dummy variables of high school completed, college degree, and dropout), the same dummy variables for the educational status of fathers, whether the child is raised by a single mother or not, home ownership status of the household, family size and race.

The second part of assumption 1 implies that the observed mediator (child health) is ignorable or random given the actual treatment status (childhood poverty) and the stated pretreatment confounders. Similarly, educational attainment is ignorable or random given the actual treatment status, pre-treatment confounders, and child health. Hence, exogeneity is assumed for the treatment T, the alternative mediators H, and the mediator of interest E.

Assumption 1 is not sufficient for the identification of the ACME in the presence of causally dependent multiple mediators. However, Robins (2003) showed that if the extra assumption of no treatment-mediator interaction effect holds on top of the sequential ignorability assumption, the ACMEs are identifiable.

Assumption 2: (No Interaction Between Treatment and Mediator)
For every unit i, we assume the following equality,
$Y_i(1, e, H_i(1)) - Y_i(0, e, H_i(0)) = Y_i(1, e', H_i(1)) - Y_i(0, e', H_i(0))$, for any e, e'.

The problem with this assumption is, it is unlikely to be credible in most applications because it must hold for every unit. In our context, it is difficult to hold this assumption since children's health capital and educational attainment have interaction with childhood poverty. Heckman and Pinto (2015) also argued that even though the Imai and Yamamoto (2013) approach is based on weaker assumptions than the Pearl (2001) solution, which is based on lack of variation of unobserved inputs (mediator in our context), their assumptions are nonetheless still quite strong.

To overcome this limitation, Imai and Yamamoto (2013) introduced the following methodology that relaxes the no-interaction assumption. Even though this remedy relaxes the second assumption, homogeneous interaction between treatment and mediator is still needed. But, the sensitivity analysis discussed below addresses the robustness of ACME for the possibility of heterogeneous interaction.

ACMEs are identified using two unobserved quantities that are used as sensitivity parameters. The first parameter is the correlation between the mediator of interest $M_i(t)$ and the individual-level treatment-mediator interaction effect κ_i i.e., $\rho_t = Corr(M_i(t, W_i(t)), \kappa_i)$. The second one is the standard deviation (SD) of the individual-level coefficient for the treatment-mediator interaction, i.e., $\sigma = \sqrt{V(\kappa_i)}$. When $\rho_t = 0$, we can identify the ACME regardless of the value of σ. However, when ρ_t, is not equal to zero, we must specify both ρ_t and σ in order to estimate the ACME under assumption 1.

Imai et al.(2010a, 2010b) used coefficients of determination as an alternative parameterization to ease interpretation of the parameters. Specifically, the proportion of the unexplained or original variance of the outcome explained by incorporating the heterogeneity in the treatment-mediator interaction has been used to substitute the function played by ρ_t. Thus, the sensitivity parameter represents how important it would be to incorporate the interaction heterogeneity in the regression model to explain the variation in the outcome variable. Formally, these parameters are defined as:

$$R^{2*} = \frac{V(\tilde{\kappa}_i T_i M_i)}{V(\eta_{3i}(T_i, M_i, W_i))} \qquad and \qquad \tilde{R}^2 = \frac{V(\tilde{\kappa}_i T_i M_i)}{V(Y_i)} \tag{29}$$

for the proportion of unexplained variance and that of the original variance explained by the heterogeneity of the treatment-mediator interaction effects, respectively. Then, it is possible to directly relate these quantities to the ACME through the following one-to-one relationship between σ and each of these coefficients of determination as:

$$\sigma = \sqrt{\frac{V(\eta_{3i}(T_i, M_i, W_i))R^{2*}}{E(T_i M_i^2)}} = \sqrt{\frac{V(Y_i)\tilde{R}^2}{E(T_i M_i^2)}} \tag{30}$$

This implies that σ is bounded from above by $\sqrt{\frac{V(\eta_{3i}(T_i, M_i, W_i))}{E(T_i M_i^2)}}$ because $0 < R^{2*} < 1$. The sensitivity to the interaction heterogeneity can be assessed by studying how the ACME varies depending on the values of R^{2*} and $\tilde{R}^2$. This can also be done by calculating the ratio of σ to its upper bound.

Yin and Hong (2019) also showed that, assuming the generalized SI and linear structural equation model (LSEM) for all measured and unmeasured variables, general average direct effect (ADE) and general average causal mediation effect (ACME) can be identified through two linear regression equations. This identification is applicable even when multiple causally-dependent mediators are unmeasured. The identification implies ADE and ACME can be easily calculated using the coefficients of the two linear regression equations.

$$ACME = E(\delta_i(t)) \equiv E[Y_i(t, M_i(1, W_i(1), W_i(t))) - Y_i(t, M_i(0, W_i(0), W_i(t)))] \tag{31}$$

$$ADE = E(\zeta_i(t)) \equiv E[Y_i(1, M_i(t, W_i(t), W_i(1))) - Y_i(0, M_i(t, W_i(t), W_i(0)))] \tag{32}$$

Hence, Average Treatment Effect (ATE) can be decomposed into ADE and ACME as:

$$\text{ATE} = \text{ADE}(0) + \text{ACME}(1) = \text{ADE}(1) + \text{ACME}(0).$$

This simply means that ATE is equivalent to $\bar{\tau} \equiv E(\tau_i)$, which is the same as the estimator of equation (27).

Generally, the estimation procedure of ACME, ADE and ATE follows the following steps as explained in Imai et al. (2010a).

(a) Fit the models for the observed outcome and mediator variables.
(b) Simulate the model parameters from their sampling distribution.
(c) Repeat the following three steps:
    (i) simulate the potential values of the mediator,
    (ii) simulate the potential outcomes given the simulated values of the mediator and
    (iii) compute the causal mediation effects.
(d) Compute summary statistics such as point estimates and confidence intervals.

Then, conduct sensitivity analysis to gauge the robustness of the potential violation of the homogeneous interaction assumption by examining how the location and width of the bounds vary as σ changes. The results from the whole procedure provide us information to test the hypotheses about the labor market outcomes discussed under the theoretical model (hypothesis 3 and hypothesis 4).

A similar average causal mediation analysis procedure was employed for the four stages of child development. The treated groups comprise individuals who lived half or more years of their life in that particular stage of poverty. The labor market outcome variables and the pre-treatment covariates are the same for the infancy stages of child development. However, the other stages of child development incorporated the poverty statuses of the previous stages as part of the pre-treatment covariates.

5 Empirical Results

5.1 Effect of Childhood Poverty on Adult Outcomes

The first step to measuring the impact of growing up poor on adult outcomes is to estimate a probit model for an individual's propensity score of being poor during childhood years. This estimation gives us the probability of a child growing up in a poor household given the observed pretreatment characteristics that are explained in the previous section. The estimated propensity score indicates that within the same value of propensity score, growing up poor or not does not depend on the values of the pretreatment characteristics. This implies that those who grew up poor and those who did not should be similar on average conditional on observable pretreatment characteristics.

Table 6 shows the probit estimate of the propensity score, that measures the effect of parental and family-level characteristics on the probability of being poor during childhood. The result shows that the propensity of an individual being poor during his or her childhood is negatively and significantly affected by parental educational attainment depending on whether parents own their own residence, the number of adults in the family, fathers' age at birth, and being White. On the other hand, the probability of facing childhood poverty is significantly pronounced if a child is raised by a single mother, has a large-sized family, and older age of mother at the time when the child was born.

Table 6: Propensity Score Estimation

	Dependent Variable: Persistently Poor
Mother's age	0.0224***
	(0.0084)
Father's age	-0.0134*
	(0.00741)
Mother HS graduate	-0.191**
	(0.0945)
Father HS graduate	-0.0510
	(0.0926)
Mother college	-0.506***
	(0.0979)
Father college	-0.345***
	(0.0991)
Single mother	0.304***
	(0.0879)
Tenancy status	-0.671***
	(0.0759)
Family size	0.199***
	(0.0288)
Number of Adult	-0.246***
	(0.0736)
White	-0.560**
	(0.270)
Black	-0.0396
	(0.271)
Constant	-0.718**
	(0.323)
χ^2	507 (12)
Pseudo R-square	0.251
N	2503

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

Important requirement for propensity score matching identification is the presence of common support, which ensures that for each treated unit (or a group comprised of individuals who grew up poor) there are control units (non-poor) with the same observables. Based on the psmatch2 matching with 0.001 caliper distance, 83 observations from the treated group are outside the common support of propensity score distributions for the two groups. This is shown in Figure 3.

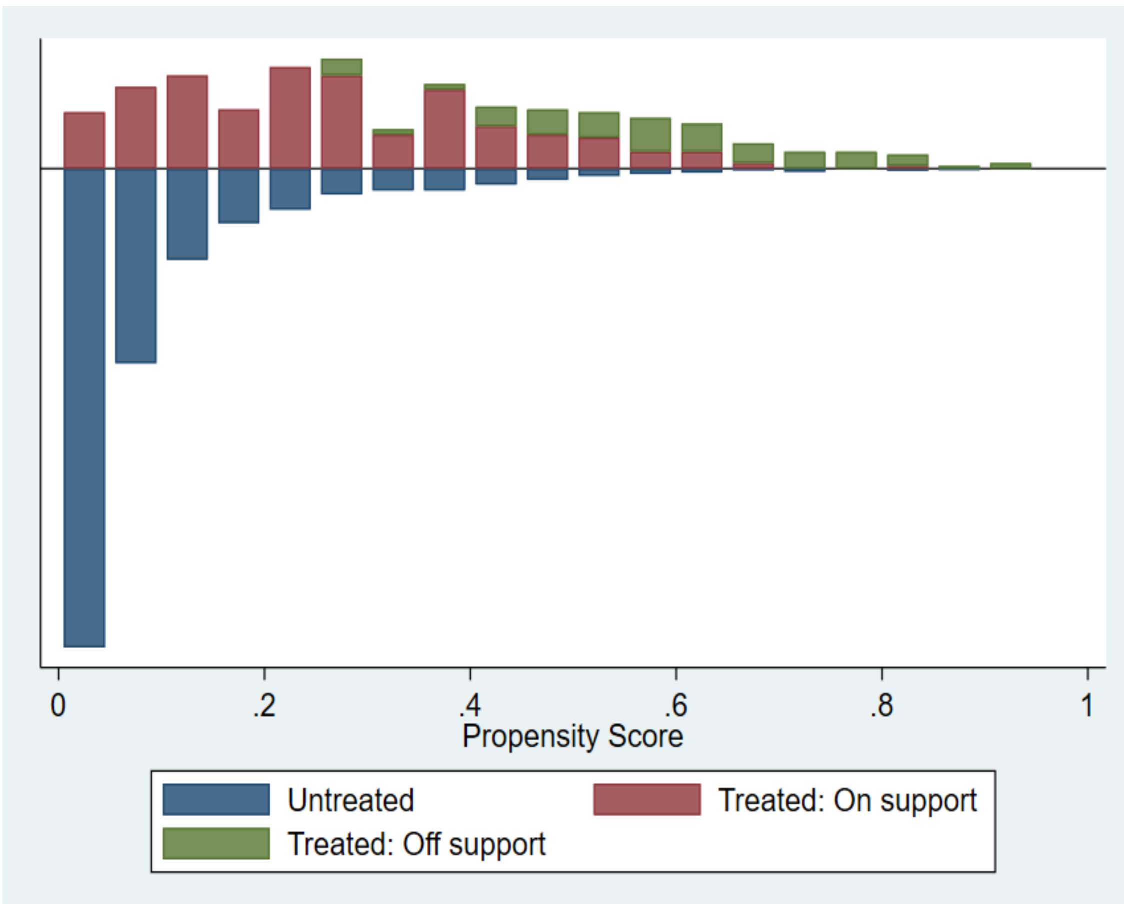

Figure 3: Common support of propensity score distribution for poor and non-poor.

After the propensity score matching, the Kernel density of the control group changed significantly and became comparable with the same distribution of the treated group. Figure 4 shows the two groups' propensity scores distributions before and after the matching.

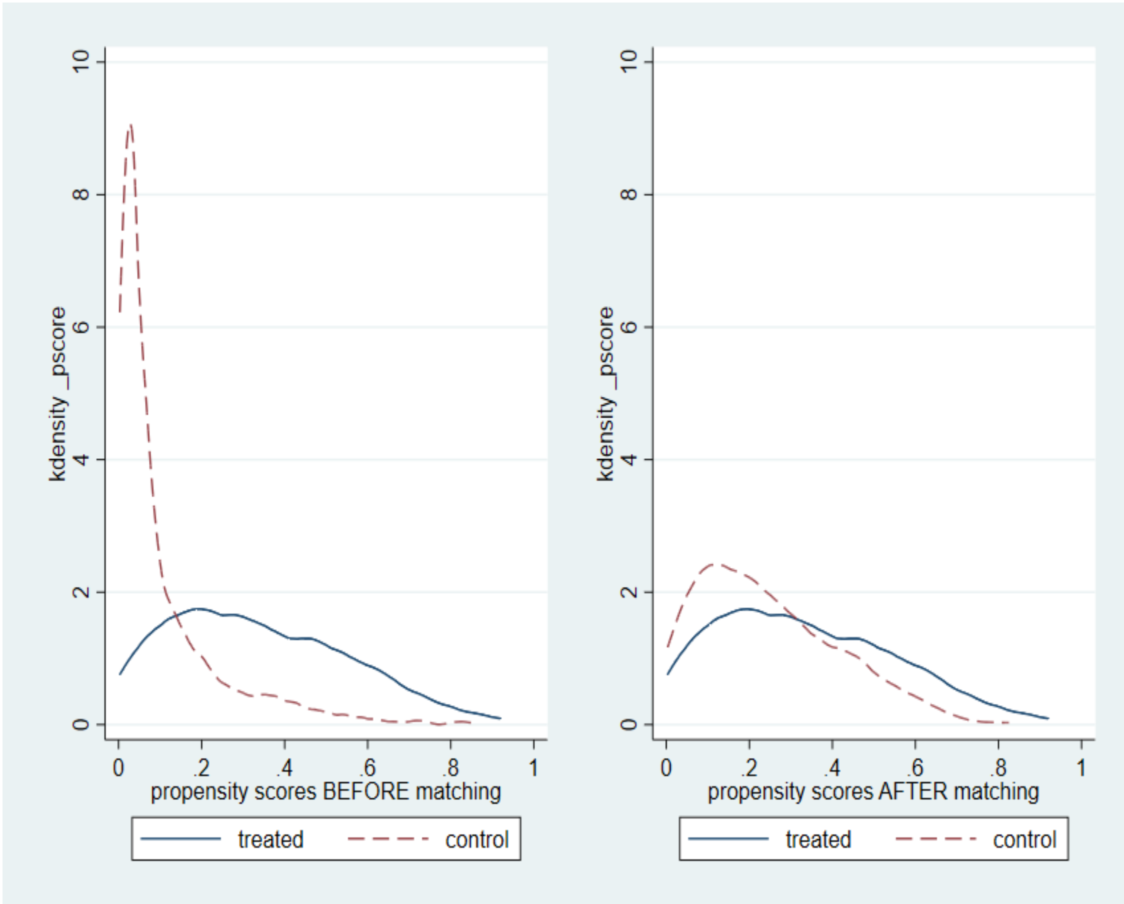

Figure 4: Propensity score density distributions before and after matching.

The statistical pstest numerical result reinforces the balance among covariates after the propensity score matching as graphically illustrated in Figure 4. Contrary to the unmatched data, which has a significant mean difference for all covariates, the matched data has significantly non-differentiable covariates. The overall chi-square measurement also showed that there are no significant covariates value differences between the treatment and control groups after the matching has been done. The mean bias after matching became very small (4.3) as compared to the mean bias before matching (50.7) as shown in Table 7.

Table 7: **Covariates Comparison of the Two Groups Before and After Matching**

Variables	Mean Difference^{+} Unmatched	Matched
Mother's age	1.531***	-0.400
Father's age	1.853***	-0.415
Mother HS graduate	0.051*	0.000
Father HS graduate	0.058**	-0.019
Mother college	-0.297***	0.015
Father college	-0.316***	0.038
Single mother	0.252***	-0.042
Tenancy status	-0.381***	-0.011
Family size	0.995***	0.085
Number of Adult	0.0584**	-0.045
White	-0.437***	0.000
Black	0.429***	-0.004
LR χ^2	507.01	4.29
Mean Bias	50.7	4.3
p-value χ^2	0.000	0.978

$^{+}$ Mean Difference of Treated (Poor=348) and control (Non-poor=2155)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Childhood Poverty and Mediator Outcomes

The mediator outcomes considered for the analysis in this section are childhood health status and educational attainment. The result presented in Table 8 shows that childhood poverty has a significant and negative effect on having a healthy childhood with a magnitude of 19.62 percentage points. This implies that the proportion of children who had a healthy childhood from the group who grew up in poverty is 19.62 percentage points smaller than the matched control (those who grew up non-poor).

Regarding education outcomes, growing up poor has significant and negative effects on years of schooling and earning a college degree and above. The proportion of individuals who have a college degree from the group of individuals who grew up poor is 12.45 percentage points less than that of those who did not. This result is in line with the non-linear evaluation of the impact of growing up poor on years of schooling. The effect of childhood poverty to attain lower levels of education is significant and negative with a relatively smaller magnitude (0.826) whereas the quadratic estimate of years of schooling indicates that it has a significant and negative effect on attainment of a higher level education with a larger magnitude (23.13).

Table 8: Average Treatment Effect of Childhood Poverty on Health and Education

	Healthy Childhood (%)	YS Linear	YS Quadratic	College (%)
ATT	-19.62***	-0. 826***	-23.13***	-12.45***
	(0.048)	(0.186)	(5.299)	(0.045)

YS is Years of Schooling. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The effect of childhood poverty is not confined to its effect on mediator variables. The long-run effect of childhood poverty on adult labor market outcomes which passes through these two mediator variables as well as the transmission mechanism that flows among them will be discussed in the next section.

5.3 Effect of Childhood Poverty and Causal Mediating Roles of Health and Education

The effects of Childhood poverty on children's health capital and education attainment transcend to other adult labor market outcomes. The focus in this section is to gauge the total effect of childhood poverty on labor market outcomes and the proportion of the effect that passes through the two mediator variables discussed earlier. We employed the causal mediation analysis procedure as explained in section 4.1.2 to determine the total effect of childhood poverty on outcome variables and its decomposition to direct and indirect effects. In addition, the proportion of the total effect which is explained by the mediating role of health and education was also measured. For all ACME estimations, 1000 simulations of potential values of the mediator and corresponding potential values of outcomes given the simulated values of the mediator have been manipulated. Then, the causal mediation effects are calculated based on the given potential values. This helps to estimate the standard errors from which the significance level of ACME and ADE estimates are drawn. The simulation type employed here is the Imai et al. (2010a) default simulation of the quasi-Bayesian Monte Carlo method based on normal approximation.

Table 9 presents ACME estimates for both the treated (poor) and control (non-poor) groups together with the weighted average ACME and the total effect of childhood poverty for three labor market outcomes: average annual values of labor income, hours worked, and the number of weeks unemployed. Childhood poverty has a significant and negative impact on average annual labor income that amounts to a total of $11,252 difference between the treated (poor during childhood) and control (non-poor during childhood) groups. And, out of this total labor income impact of childhood poverty, 42.25 percent of its proportion is transmitted through its negative effect on child health and education.

Table 9: ACME and Total Effect of Childhood Poverty on Labor Market Outcomes

	Labor Income	**Hrs Worked**	**Wks Unemployed**
Average Causal Mediation Effect	**-4,754*****	**-41.1*****	**0.4268****
	[-8057, -1450]†	[-71.7, -10.6]	[0.018, 0.84]
% of total effect mediated	**42.25**	**22.57**	**21.73**
Causal Mediation Effect (poor)	-4,402	-65**	0.6373*
	[-10794, 1990]	[-119.5, -10.5]	[0.0687, 1.34]
% of total effect mediated	39.12	35.69	32.45
Causal Mediation Effect (non-poor)	-4,810***	-37.3***	0.3936**
	[-7711, -1910]	[-64.5, -10.0]	[0.0275, 0.76]
% of total effect mediated	42.75	20.48	20.04
Total Effect	**-11, 252****	**-182.1*****	**1.964*****
	[-21087, -674]	**[-269.2, -90.6]**	**[0.952, 3.09]**

†95% confidence intervals. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similarly, growing up poor has negative impacts on other labor market outcomes. It has a significant and negative effect on average annual hours worked and a significant and positive impact on the annual average number of weeks an individual stays unemployed in a year. The figures are 182.1 hours and 1.96 weeks, respectively.

From the estimates for average annual hours worked and the average number of weeks unemployed, the indirect effect or ACME of mediator variables (health and education) constitutes a significant portion of the total effect of childhood poverty, both in terms of magnitude and significance. Out of the total effect of childhood poverty on annual hours worked, 41.1 hours reduction or 22.57 percent passes through its negative influence on a child's health and education. This magnitude is even larger when the treatment effect is calculated only on the poor (treated) group that is 65 hours or 35.7 percent. The ACME and total effect estimation of the number of weeks unemployed showed that a significant portion of the effect of childhood poverty passes indirectly through its influence on child health and education before it affected the outcome variable. It constitutes 21.73 percent of the total effect and is highly significant. This estimation is more pronounced when it is calculated with respect to the counterfactual constructed from those who grew up poor (32.45 percentage points). Figure 5 demonstrates these quantitative results.

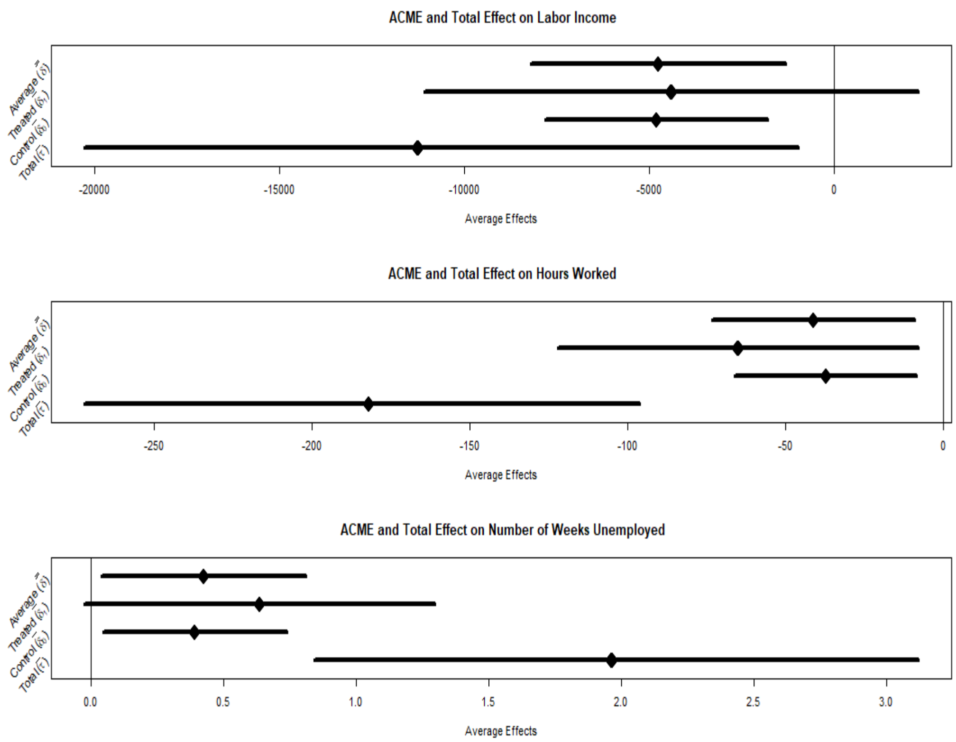

Figure 5: ACME and total effect on labor market outcomes with 95% CI.

5.4 Gender Disaggregated Analysis of Impact of Childhood Poverty

The labor market experiences of women and men differ in terms of earnings and labor force participation (the U.S. Bureau of Labor Statistics, 2017). Hence, this section deals with the gender disaggregation of the impact of childhood poverty on labor market outcomes. The study has 1,303 women and 1,200 men, out of which 217 women and 131 men experienced persistent poverty during their childhood.

The disaggregation is done in two possible combinations of gender and poverty statuses; viz., poor women vs. non-poor women and poor men vs. non-poor men. As the estimates for both possible combinations presented in Table 10 show, individuals who experienced childhood poverty performed less. Experiencing childhood poverty has a negative effect on labor income, hours worked and the number of weeks unemployed. The total labor income effect ($12,820) of childhood poverty is larger for women (i.e. when comparing persistently poor women with non persistently poor women) than men (persistently poor men vs non persistently poor men). Out of the total effect of childhood poverty ($12,820), 39.78% of the effect passes indirectly through the two mediator outcomes.

On the other hand, the total effects of childhood poverty on both the other two labor market outcomes are larger for men. The total hours worked difference between not persistently poor men and persistently poor men is 264.64 hours. Similarly, the number of weeks unemployed difference between men who experienced persistent poverty during their childhood and those who were not is 2.45 weeks. A similar comparison number of weeks unemployed per annum between women who experienced persistent poverty during their childhood and those who were not is 1.86 weeks.

Table 10: Gender Disaggregated Impact of Childhood Poverty

Comparison Groups	Effect	Labor Income	Hours Worked	Weeks Unemployed
	Total Effect	-12,820***	-62.752	1.86***
Women	ACME	-5,100***	-67.149***	0.3483
	% of ACME	**39.78**	**107.01**	**18.73**
	Total Effect	-7,124	-264.64***	2.45**
Men	ACME	-6,539	-7.30	0.6554*
	% of ACME	**91.79**	**2.76**	**26.75**

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

5.5 Poverty at Different Stages of Child Development and Its Effect

Childhood poverty considered in the previous section is persistent poverty in which a child spends more than half of his or her childhood ages in poverty. It crosses more than one stage of child development. Hence, the focus of the analysis in this section is to measure the effect of childhood poverty confined to a single stage of child development. This enables us to identify which stage is most critical in terms of having a long-run effect. The previous stages of child poverty statuses are considered as pretreatment covariates when estimating the effect of childhood poverty for each stage of child development.

As the estimation results in Table 11 show, for all health and education-related mediator outcomes, poverty during early childhood has the largest and significant negative effect as compared to poverty that occurs at any other stages of child development. The PSM estimation results showed that the proportion of individuals who had a healthy childhood and attain a college degree is significantly lower (by 16.04 percent and 11.19 percent, respectively) for the group who experienced persistent poverty during early childhood as compared to those who did not. Hence, the early childhood stage is critical in terms of the long-run effects of poverty on health and educational attainment.

Table 11: Effect of Childhood Poverty at Different Stages of Child Development

	Healthy Childhood	**YS†**	**SYS††**	**College Degree**
Infancy	-8.2	-0.041	-2.09	-4.1
	(0.061)	(0.256)	(7.25)	(0.059)
Early Childhood	-16.04***	-0.709***	-20.08***	-11.19***
	(0.047)	(0.18)	(5.20)	(0.046)
Mid-Childhood	-6.19	-0.454 **	-12.21*	-4.12
	(0.056)	(0.223)	(6.35)	(0.055)
Late Childhood	-2.7	-0.195	-5.75	-5.84
	(0.048)	(0.192)	(5.527)	(0.049)

†Years of Schooling †† Square of Years of Schooling Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The causal mediation analysis in Table 12 also shows that poverty at all stages of child development, with the exception of infancy, has a significant reduction effect on hours worked with magnitudes of 117.5, 178, and 92.1 hours, respectively. Out of these total effects of childhood poverty, 35.74, 27.47, and 25.84 percent, respectively, channeled through its negative effect on health and education (or the proportions are ACME or indirect effect). However, there is no strong evidence that supports childhood poverty at these stages impacts adult labor income. On the other hand, poverty during the middle childhood stage of child development has a significant total effect on the number of weeks unemployed (1.18 weeks).

There is no strong evidence for the impact of poverty during infancy on adult hours worked and the number of weeks unemployed. Similarly, there is no strong evidence for the impact of poverty during early childhood and late childhood on the number of weeks unemployed. Table 12 shows ACME estimation results for childhood poverty that lasts for only a single stage of child development.

Table 12: ACME for Different Stages of Child Development

		Labor Income	Hours Worked	Weeks Unemployed
Infancy	TE	-13,500***	-46.29	0.5806
		[-20609, -5962]†	[-181.93, 89.7]	[-0.802, 2.11]
	ACME	-1,871	-39.37	0.47
		[-5608, 1866]	[-95.72, 17]	[-0.1151, 1.05]
Early Childhood	TE	-7,696	-117.5***	0.748
		[-16126, 4070]	[-198.8, -34.1]	[0.17, 1.71]
	ACME	-4,079***	-42***	0.361***
		[-6542, -1615]	[-66.9, -17]	[0.0878, 0.63]
Mid-Childhood	TE	-7,820*	-178***	1.18**
		[-15,560, 896]	[-291.7, -74.14]	[0.1025, 2.32]
	ACME	-2640	-48.9***	0.418**
		[-6271, 992]	[-83.6, -14.19]	[0.007, 0.83]
Late Childhood	TE	-6,904	-92.1**	0.76
		[-15442, 2452]	[-184.2, -2.21]	[-0.3317, 1.82]
	ACME	-1281	-23.8**	0.362**
		[-3635, 1073]	[-42.2, -5.43]	[0.0855, 0.64]

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
†95% confidence intervals are in square brackets.

5.6 Sensitivity Analysis

The causal mediation estimation carried out in the previous section falls under the two untestable assumptions: sequential ignorability and homogeneous treatment-mediator interaction assumptions. This section deals with the sensitivity of the estimation results when these assumptions are relaxed. One of the important parameters to make the sensitivity analysis is . It represents the correlation across the two error terms of outcome and mediator equations. If the sequential ignorability assumption holds, all relevant pre-treatment confounders have been conditioned on and thus equals zero. The nonzero values of imply departures from the sequential ignorability assumption and that some hidden confounder is biasing the ACME estimate.

The key concern in this study is an unmeasured confounder that affects both mediator and outcome variables. For instance, a child's ability can affect both his educational achievement and labor market outcomes later in life. Any confounding of this type will be reflected in the data-generating process as a correlation between the two error terms. Ignoring this and estimating the two models separately will lead to a biased estimate of the ACME. Thus, can serve as a sensitivity parameter since larger extreme values of represent more departures from the sequential ignorability assumption. Because the true parameter value of this coefficient is unknown and its interpretation is relatively difficult, the coefficients of determinations of the two models play equivalent roles. The first coefficient of determination is the proportion of the total variance of labor market outcomes that would be explained if we consider the heterogeneity of the treatment–mediator interaction (childhood poverty and educational attainment) in the regression model (R^{2t}). The second coefficient of determination is the proportion of unexplained variance explained by an additional term for interaction heterogeneity (R^{2*}).

For example, if a confounder is important in determining the level of education and the labor market outcome measures, then the models excluding the confounder will have a much smaller value of R^2 compared to a model including the confounder. On the other hand, if the confounder is unimportant, R^2 will not be very different whether including or excluding the variable. Thus, this relative change in R^2 can be used as a sensitivity parameter to check the robustness of ACME estimates.

The other parameter used for the sensitivity analysis is the standard deviation (SD) of the individual level coefficient for the treatment-mediator interaction (childhood poverty and educational achievement). Other things remaining equal, a low value of this upper bound indicates a more robust estimate of the ACME since it leaves less room for an unobserved confounder to bias the result.

Table 13 presents ACME's sensitivity parameter estimates of the weighted average of the treated (poor) and control (non-poor) groups. The other details of sensitivity analysis for the treated and control groups' estimates are annexed in Appendix 1A.

Table 13: Sensitivity Parameter Estimates of ACME on Treated

	σ (**b**)†	$\mathbf{R^{2}*(b)}$	$\mathbf{R^{2t}(b)}$
Labor Income	3,130	0.03	0.0288
Hours Worked	25.262	0.04	0.0396
Number weeks Unemployed	0.272	0.06	0.0569

† **b**s in the columns name refer to bounds of the sensitivity parameters.

The Labor income sensitivity parameter estimates show that ACME does not become positive until σ becomes greater than 3,130, or 41.4 percent of its largest possible value given the data (7,550). This implies that the ACME estimate still provides some support for the important mechanism that links childhood poverty with labor market outcomes even after we allow a certain degree of violation of the no interaction assumption. The corresponding coefficients of determination estimates are 3 and 2.88 percent, respectively. The estimated values are too small and they require unobserved confounders that are not in the model would need to explain 97 percent or more of the remaining variation in education (main mediator) and labor income (outcome) for the ACME to lose its statistical significance.

The Hours Worked sensitivity parameter estimates show that ACME does not become positive until σ becomes greater than 25.262, or 25 percent of its largest possible value (101.05). The corresponding coefficients of determinations are 4 and 3.96 percent, respectively. These estimates are very small and require confounders that are not incorporated in the model would need to explain 96 percent or more of the remaining variation in education (main mediator) and hours worked (outcome) for the ACME to lose its statistical significance. This is a strong indication of the robustness of ACME estimation. It provides a great deal of room to relax both homogeneous interactions as well as sequential ignorability assumptions. Hence, there is strong evidence for the negative causal mediation impact of poverty on hours worked through its negative effect on childhood health and level of education.

A similar conclusion also can be drawn about the Number of Weeks Unemployed. It has a sigma bound of 0.271, that is 24.49 percent of 1.12 (the largest possible value) and the corresponding coefficients of determinations are 6 and 5.96 percent, respectively. This leaves less room for unobserved confounders to bias the estimation. Hence, there is robust evidence about the positive indirect effect (ACME) effect of childhood poverty on the number of weeks unemployed which passes through its negative effect on health and education.

Figure 6 graphically shows the quantitative analyses discussed so far. The broken lines indicate ACME estimates, and the solid lines are sensitivity analysis parameters. The gray area is the 95 percent confidence interval. The graphical details of the sensitivity analysis for total, direct and indirect effects are annexed in Appendix 1A through 1D.

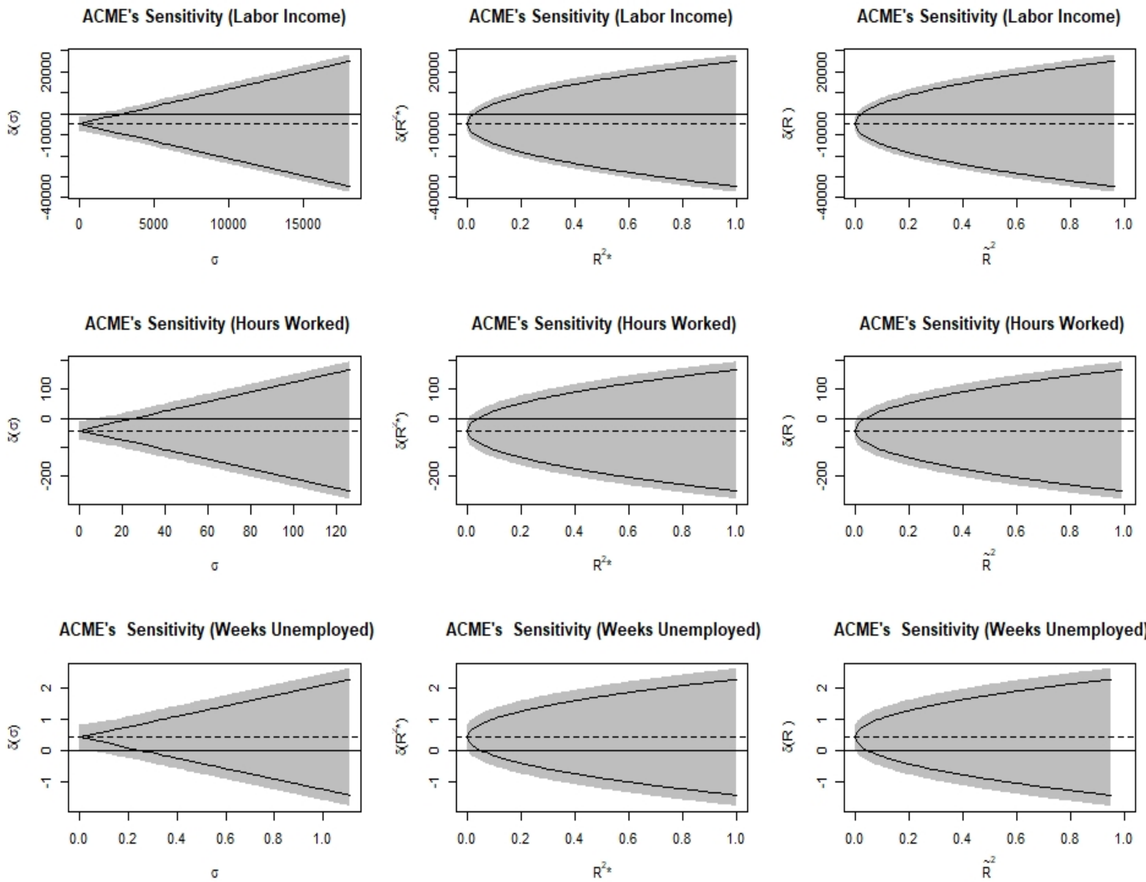

Figure 6: ACME Sensitivity Analysis Plots.

The other sensitivity analysis considered in the study is done after altering the poverty line. The 125 percent of the federal poverty line value is taken to differentiate the treated (those who grew up in a household that had an annual family income below the threshold) and control (who had above the threshold) groups. The propensity score matching estimate of persistent childhood poverty showed that childhood poverty significantly and negatively affects childhood health and educational attainment (mediator outcomes). As Table 14 shows, the proportion of children who had a healthy childhood from the group who grew up in poverty is 20 percentage points smaller than the matched control (those who grew up non-poor). Similarly, the proportion of individuals in the treated group who have a college degree is 15.45 percentage points less than that of those in the control group.

Table 14: Average Treatment Effect of Childhood Poverty on Health and Education

	Healthy Childhood (%)	YS Linear	YS Quadratic	College (%)
ATT	-20***	-0. 694***	-19.86***	-15.45***
	(0.042)	(0.159)	(4.573)	(0.041)

YS is Years of Schooling. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The ACME estimates also show that higher values of the poverty line reinforce the long-run impact of childhood poverty on labor market outcomes. As Table 15 presents, growing up poor has a significant and negative impact on average annual labor income, which amounts to a total of $14,672 difference between the treated (poor during childhood) and control (non-poor during childhood) groups. Out of this total labor income impact of childhood poverty, 18.7 percent of its proportion is transmitted through its negative effect on child health and education.

Similarly, growing up poor has a negative impact on other labor market outcomes. It has a significant and negative effect on average annual hours worked and a significant and positive impact on the annual average number of weeks an individual stays unemployed in a year. The figures are 159 hours and 1.99 weeks, respectively.

Table 15: ACME and Total Effect of Childhood Poverty on Labor Market Outcomes

	Labor Income	Hours Worked	Weeks Unemployed
ACME	**-2,745*** **	**-33.5*** **	**0.464*** **
% of total effect mediated	**18.7**	**21.07**	**23.32**
Total Effect	**-14, 672** **	**-159*** **	**1.99*** **

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

A similar estimation of the effects of childhood poverty, using 125 percent of the federal poverty line, is computed for the four stages of child development and presented in Table 16. The results show that all health and education-related mediator outcomes, poverty during each stage of child development has a negative effect. Particularly, childhood poverty during early childhood and middle childhood stages has consistently significant negative effects compared to poverty that occurs in other stages of child development.

Table 16: Effect of Childhood Poverty at Different Stages of Child Development

	Healthy Childhood	YS†	SYS†	College Degree
Infancy	-9.326*	-0.347*	-10.27*	-7.77
	(0.052)	(0.211)	(5.974)	(0.049)
Early Childhood	-10.23**	-0.664***	-18.904***	-13.45***
	(0.042)	(0.161)	(4.634)	(0.041)
Mid-Childhood	-8.65*	-0.547 ***	-15.44**	-9 *
	(0.05)	(0.197)	(5.63)	(0.049)
Late Childhood	-11.14**	-0.285	-8.801*	-11.14**
	(0.046)	(0.182)	(5.248)	(0.046)

†Years of Schooling. †† Square of Years of Schooling.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The causal mediation analysis results in Table 17 also show that poverty at all stages of child development, with the exception of infancy, have a significant reduction effect on hours worked with magnitudes of 90.5, 132.5 and 72.4 hours, respectively, in their sequential order. There is also strong evidence supporting the conclusion that poverty during the first three stages of child development has a negative and significant impact on annual labor income. Furthermore, poverty during the early and middle childhood stages of child development has a positive and significant total effect of number of weeks unemployed (1.19 and 0.785 weeks, respectively).

Table 17: ACME for Different Stages of Child Development

		Labor Income	Hours Worked	Weeks Unemployed
Infancy	TE	-12,414***	-65.5	0.786
	ACME	-459	-25.7	0.506**
	%	3.7	39.24	64.38
Early Childhood	TE	-9,415***	-90.5**	1.19***
	ACME	-3,340***	-29.8***	0.266***
	%	35.48	32.93	22.35
Mid Childhood	TE	-8,628*	-132.5***	0.785*
	ACME	-331	-34.9***	0.427**
	%	3.84	26.34	54.39
Late Childhood	TE	-2,671	-72.4*	0.646
	ACME	-356	-13.5**	0.284**
	%	13.33	18.65	43.96

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

6 Discussions and Conclusion

Using PSID's intergenerational survey data, in this paper I have evaluated the mediator and long-run effects of growing up poor. Propensity score matching and ACME estimations were employed to measure the interaction among childhood poverty, mediator variables, and labor market outcomes. The propensity score matching estimates showed that childhood poverty has a significant and negative effect on health status. This finding is consistent with some of the literature reviewed in section 2 (Currie & Almond, 2011; Duncan et al., 1998; Levy & Duncan, 2000; Ziol-Guest et al., 2012).

Similarly, the findings of the effects of childhood poverty on years of education is negative and significant. Furthermore, the propensity score matching estimates showed strong evidence that supports childhood poverty has a negative effect on higher-level educational attainment. The proportion of children who have a college degree among those who grew up poor is 12.45 percentage points less than the proportion of individuals who have a college degree among those who grew up nonpoor. This result matches with the findings of some of the literature reviewed under section 2 (Chaudry & Wimer, 2016; Dahl & Lochner, 2012; Kubilius & Corwith, 2018). The estimated results for linear and quadratic values of years of schooling reinforce the non-linear effect of childhood poverty on educational attainment. The potential explanation for the mixed result of childhood poverty on lower and higher levels of education may be the U.S. education policy. The policy enables children to enroll in school without direct financial outlay but it is difficult to attend higher levels of education for those with disadvantaged economic backgrounds.

The ACME estimation results showed that persistent childhood poverty has a strong and negative total effect on annual labor income, annual hours worked, and the number of weeks unemployed per annum. From the total effect of childhood poverty on the labor market outcomes, a significant portion passes indirectly through the two mediator variables: education and child health. Individuals who grew up poor have a lower level of average annual labor income as compared to those who did not grow up poor, which amounts to \$11,252. More than 42 percent of the total effect on annual labor income is channeled through the negative effect of poverty on childhood health and educational attainment. Similarly, the total effects on average hours worked and the number of weeks unemployed are 182.1 hours and 1.964 weeks, respectively, and 22.57 and 21.73 percent of the totals are channeled through the negative effect of poverty on childhood health and educational attainment.

These significant and negative effects of childhood poverty on employment and earning are in line with some of the literature reviewed for this study (Gregg et al., 1999; Lesner, 2018; Ratcliffe & McKernan 2010, 2012). Using data from various European countries, Bellani and Bia (2019) showed that childhood poverty leads to low-income adulthood and a higher average probability of being poor. But, they used a single dummy mediator in their analysis.

The gender disaggregation analysis based on the two possible combinations of gender and poverty statuses (poor women vs. non-poor women and poor men vs. non-poor men) showed annual labor income differences ($12,820) is larger for comparison between women. On the other hand, the total effects of childhood poverty on both the other two labor market outcomes are larger for men. The total hours worked difference between persistently poor men and those who are not is 264.64 hours. Similarly, the number of weeks unemployed difference between men who experienced persistent poverty during their childhood and those who were not is 2.45 weeks. The results show significant differences for labor market outcome gaps for poor and non-poor comparison for women and men. It indicates a significant role gender plays to explain the long run effect of childhood poverty on labor market outcomes.

Similar propensity score matching and average causal mediation analysis of childhood poverty were carried out for different stages of child development. The PSM results showed that experiencing poverty during early childhood significantly deteriorates the health and education capital of a child. The result indicates that the early childhood stage is a critical period as far as the impact of financial difficulty on mediator outcome variables is concerned. This finding matches with studies based on the US data (Duncan et al., 2012; Duncan & Magnuson, 2013; Ziol-Guest et al., 2012) and is contrary to Lesner's (2018) findings which are based on data from Denmark. Furthermore, the ACME estimation results showed that childhood poverty that occurs during the three childhood stages has a negative impact on hours worked both directly and indirectly through health and education.

Evaluating the transmission mechanism of childhood poverty to adult labor market outcomes is important, as it informs policymakers about how to tailor interventions that positively influence children's health outcomes and educational achievement that in turn improve adult labor market outcomes. ACME estimates and the transmission mechanism of effect from childhood poverty to adult labor market outcomes indicate that policy intervention on child health and education has both employment and labor income implications.

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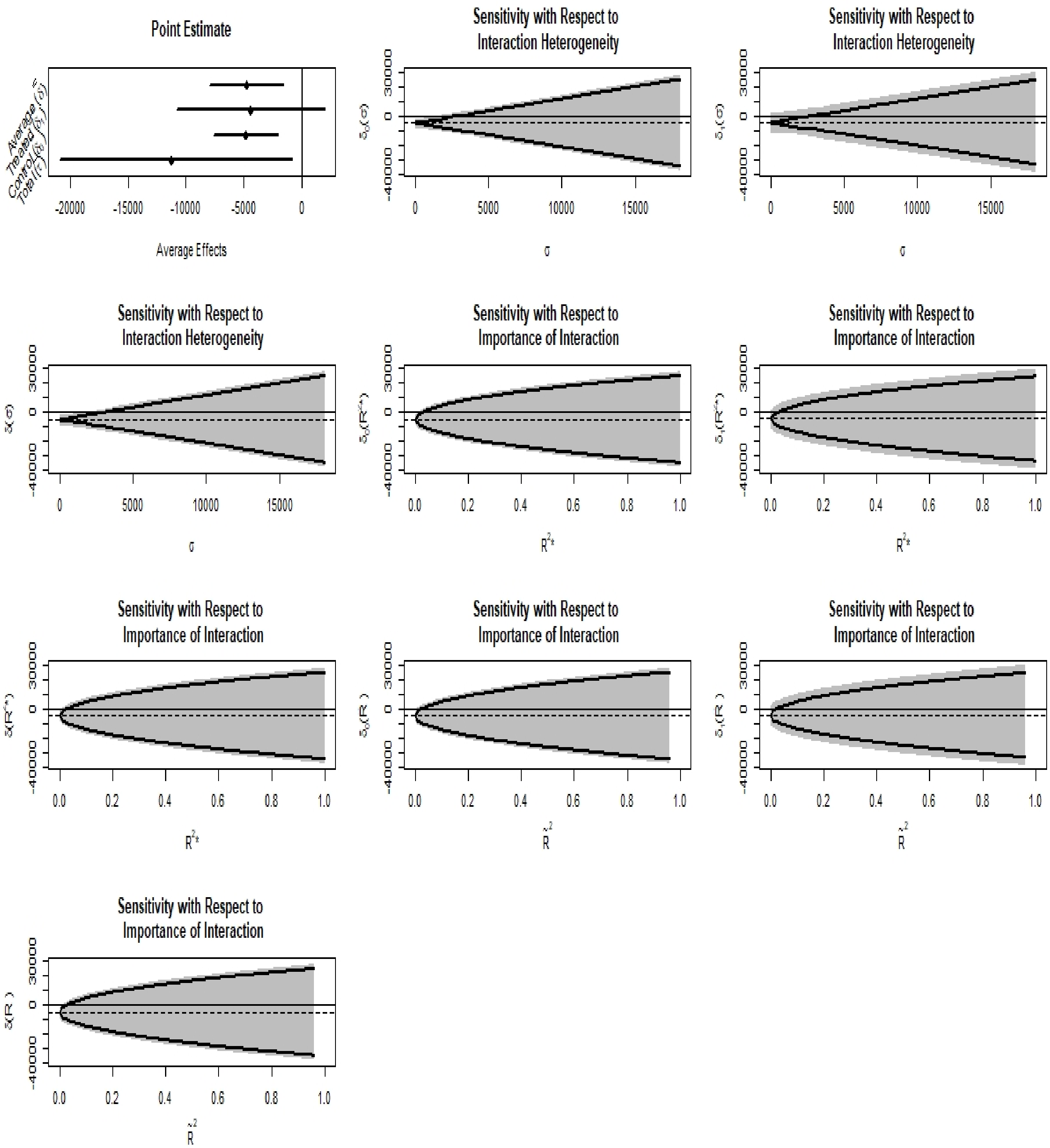
Appendices

Appendix 1A: Sensitivity Analysis Estimates of Outcome Variables

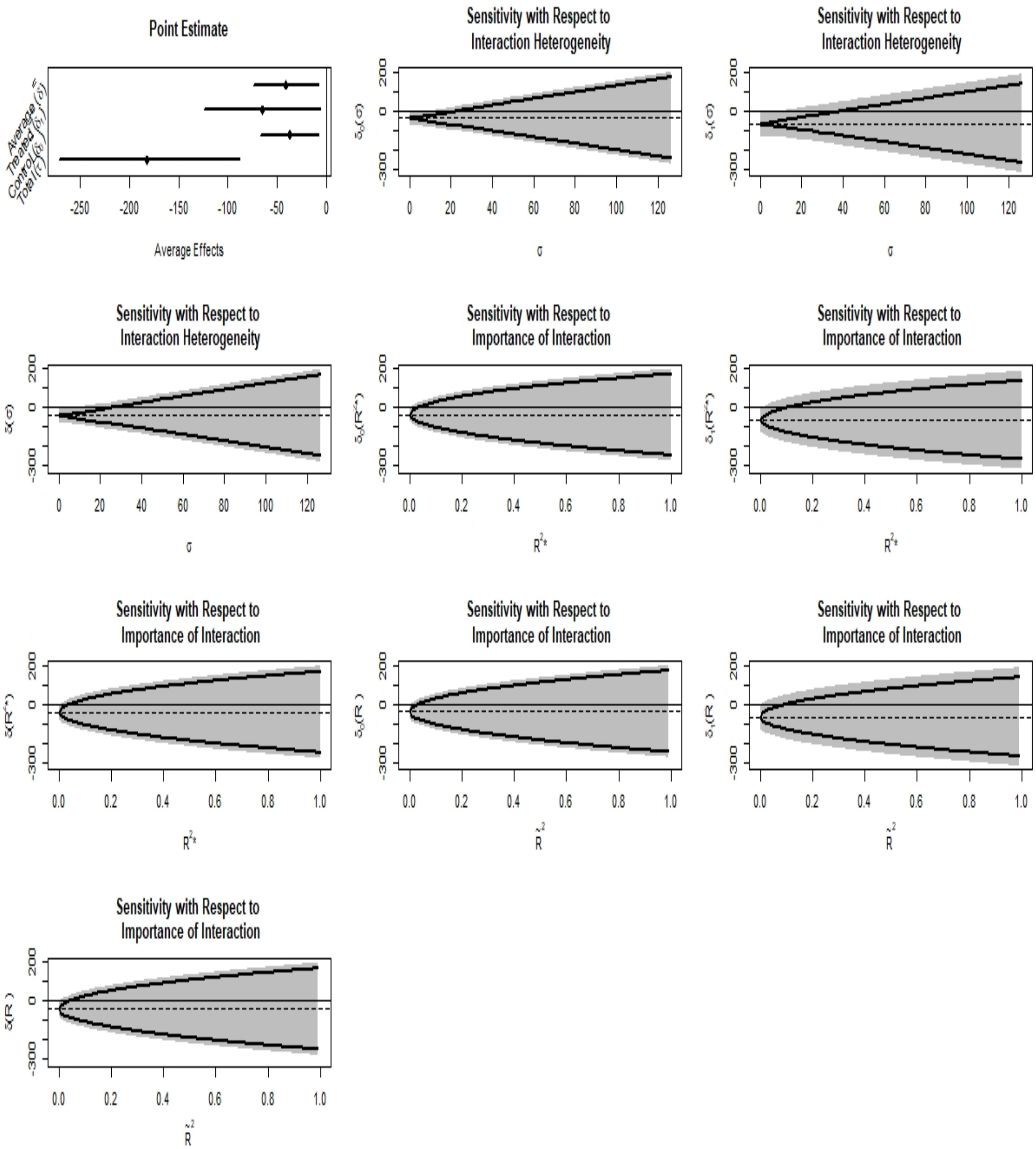
		σ **(b)**	$\mathbf{R^{2*}(b)}$	$\mathbf{R^{2t}(b)}$
Labor Income				
ACME	(treated)	3130	0.0300	0.0288
	(control)	3130	0.0300	0.0288
	(average)	3130	0.0300	0.0288
Hours Worked				
ACME	(treated)	41.89	0.1100	0.1090
	(control)	26.48	0.0400	0.0396
	(average)	29.60	0.0400	0.0396
Number Weeks Unemployed				
ACME	(treated)	0.3997	0.1300	0.1232
	(control)	0.2479	0.0500	0.0474
	(average)	0.2715	0.0600	0.0569

Columns identified by **b** are bounds of the sensitivity parameters.

Appendix 1B: Sensitivity Analysis for Labor Income



Appendix 1C: Sensitivity Analysis for Hours worked



Appendix 1D: Sensitivity Analysis for Number of Weeks Unemployed