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Age Trajectories of Poverty During Childhood and High School Graduation

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Abstract: This article examines distinct trajectories of childhood exposure to poverty and provides estimates of their effect on high school graduation. The analysis incorporates three key insights from the life course and human capital formation literatures: (1) the temporal dimensions of exposure to poverty, that is, timing, duration, stability, and sequencing, are confounded with one another; (2) age-varying exposure to poverty not only affects, but also is affected by, other factors that vary with age; and (3) the effect of poverty trajectories is heterogeneous across racial and ethnic groups. Results from the Children of the National Longitudinal Survey of Youth show that any extended exposures to poverty substantially lower children's odds of graduating from high school. Persistent, early, and middle-to-late childhood exposures to poverty reduce the odds of high school graduation by 77 percent, 55 percent, and 58 percent, respectively, compared to no childhood exposure to poverty. The findings thus suggest that the impact of poverty trajectories is insensitive to observed age-varying confounders. These impacts are more pronounced for white children than for black and Hispanic children.

Keywords: poverty trajectory; childhood; age-varying confounding; educational attainment; life course

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The link between poverty and children's life chances has long attracted attention in the social sciences (Aber et al. 1997; Brooks-Gunn and Duncan 1997). Exposure to poverty is posited to have negative consequences for child attainment because of resource deficits, strained parent–child relationships, increased exposure to lower-quality schools and neighborhoods, and sociocultural exclusion (Brooks-Gunn, Klebanov, and Duncan 1996; Guo and Harris 2000; McLeod and Shanahan 1993). Despite these articulated mechanisms, studies using snapshot measures of poverty typically find at best modest effects and consequently suggest that genetic endowments, family background, and parenting may explain more variation in child outcomes than economic deprivation (Blau 1999; Mayer 1997).

Meanwhile, more recent research contends that small poverty effects may stem from the imperfect conceptualization and measurement of childhood poverty. Single-point-in-time measures of economic disadvantage likely underestimate its effects because such measures conflate economic deprivation at a given time with chronic economic deprivation (Duncan et al. 1998). Research that utilizes longitudinal measures attends to poverty's temporal dimensions, documenting that when its timing, duration, stability, or sequencing is taken into account, growing up in poverty is more detrimental to children than when static measures are used (Duncan and Brooks-Gunn 1997).

However, researchers adopting the temporal perspective to date have produced mixed results. A majority of studies document that, with respect to child developmental and educational outcomes, children experiencing early and persistent poverty fare worse (Aber, Jones, and Raver 2006; Brooks-Gunn and Duncan 1997), whereas other studies report that children experiencing late and intermittent poverty are more likely to fall behind (Guo 1998; NICHD Early Child Care Research Network 2005).

These inconclusive findings raise several substantive concerns about temporal patterns of exposure to poverty. First, few studies examine the temporal dimensions of poverty, namely, timing, duration, stability, and sequencing, as a whole (but see Wagmiller et al. 2006). Consider the timing of exposure to poverty. The finding of the relative importance of early childhood poverty begs a question: Does early childhood poverty have independent effects regardless of the duration of experiencing poverty, or does it merely foreshadow persistent poverty? Second, most research on childhood poverty considers age-dependent exposure to poverty as the sole age-varying factor affecting child outcomes. Virtually all studies make an implicit assumption that only age-constant characteristics are responsible for selection into different exposures to poverty over time. Does this assumption hold when other age-varying factors affecting child outcomes (e.g., family structure) are present? Third, much research is concerned with racial/ethnic differences in the impacts of childhood poverty (Bolger et al. 1995; McLeod and Nonnemaker 2000). As racial/ethnic minority groups living in poverty are more likely than their white counterparts to face concomitant exposures to structural disadvantage (e.g., living in a disadvantaged neighborhood) and a multitude of stressful life events (e.g., family instability), poverty effects are likely to vary by race/ethnicity. Yet we know little about how temporal patterns of childhood poverty have differential impacts across racial/ethnic groups.

This article uses data from the Children of the National Longitudinal Survey of Youth (CNLSY) to investigate how distinct age patterns of exposure to poverty influence children's odds of graduating from high school, which plays a central role in the intergenerational transmission of economic disadvantage (Goldthorpe and Jackson 2008). Building on the life course and human capital formation literature (Elder 1985, 1998; Heckman 2007; Mortimer and Shanahan 2003), this study reconceptualizes exposure to childhood poverty: (1) each temporal dimension of exposure to poverty is confounded with the others; (2) age-varying exposure to poverty has dynamic relationships with other age-varying factors affecting child attainment; and (3) the effect of poverty trajectories is heterogeneous across racial/ethnic groups.

To incorporate this updated life course perspective into analysis, the present study first uses finite mixture modeling to identify distinct trajectories of exposure to poverty during childhood (Muthén 2004; Wagmiller et al. 2006). This modeling is designed such that children in the same trajectory are most likely to experience a similar pattern of poverty exposure in terms of its timing, duration, stability, and sequencing. Second, the analysis then employs propensity score weighting to sequentially balance children in poverty and children not in poverty on prior poverty history and observed age-constant and age-varying covariates (Robins 1999; Robins, Hernán, and Brumback 2000). Under the assumption of no unobserved confounding, it allows for assessing the bias that can arise in estimating the effect of poverty trajectories without proper adjustment for age-varying covariates. Third, this study estimates poverty effects separately by race/ethnicity, given differential levels of concentration of poverty across racial/ethnic groups (Wilson 1987).

Temporal Dimensions of Exposure to Poverty

The research focus on how economic deprivation is structured over time is driven by the recognition that the timing of events and transitions plays a critical role in constituting the life course (Elder, Johnson, and Crosnoe 2003) and that family income is particularly volatile for children in poor families (Duncan 1988). Numerous studies have examined various dimensions of age-dependent exposure to poverty and their associations with child development and attainment.

First, the timing of exposure to poverty has garnered much interest. The sensitive-critical period perspective argues that early childhood poverty is more detrimental than late childhood poverty to child attainment, given the malleability of young children's cognitive and socioemotional development and the overwhelming importance of the family context during early childhood (Duncan, Ziol-Guest, and Kalil 2010; Shonkoff and Phillips 2000). Children's preschool years are considered a critical period for development, as any deficits in these formative years have lingering impacts on subsequent attainment. A majority of studies confirm the so-called scar effects of early childhood poverty (Duncan and Brooks-Gunn 1997; Duncan et al. 1998).

The strained transition perspective provides a contrasting view on the timing of exposure to poverty. It holds that the negative impacts of early childhood poverty are likely to dissipate as children's developmental impairments during their early life stages recover over time, while late childhood poverty tends to complicate children's transition to adulthood as a proximate stressor (McLeod and Shanahan 1993; NICHD Early Child Care Research Network 2005). Late childhood poverty thus may be more likely to exacerbate children's motivation for academic achievement and impose pecuniary constraints on subsequent schooling (Guo 1998; Haveman, Wolfe, and Spaulding 1991).

Second, research on the duration of exposure to poverty addresses how the length of time living in poverty affects child attainment. As longer poverty spells represent an enduring lack of economic resources and chronic stress, persistent poverty is thought to be most harmful to child well-being (Korenman, Miller, and Sjaastad 1995; McLeod and Shanahan 1996). Long-term childhood poverty is closely related to early childhood poverty from the cumulative disadvantage perspective, because the onset of poverty in children's early life sets the stage for subsequent poverty throughout childhood, engenders a concatenation of negative events and influences, and reinforces enduring dispositions in social interaction (Caspi, Bem, and Elder 1989; Ratcliffe and McKernan 2010).

Third, a concern with the (in)stability of childhood economic condition, however, puts the effects of persistent poverty in perspective. If frequent moving in and out of poverty creates continuous adaptation problems for families, while poor families establish stability in family processes after the initial shock of first entry into poverty, intermittent poverty may be more detrimental than persistent poverty to children (Elder and Caspi 1988; Moore et al. 2002).

Fourth, the sequencing of exposure to poverty pertains to systematic changes in economic deprivation over time. Moving into poverty may not only strain economic conditions but also disrupt parent–child relationships, resulting in worse child outcomes. Moving out of poverty may either improve child well-being by generating procyclical family processes between economic circumstances and parent–child relationships or still relate to negative child outcomes because of lingering effects of early childhood poverty (Conger, Conger, and Elder 1997; Dearing, McCartney, and Taylor 2001).

Age Trajectories of Exposure to Poverty

The competing theoretical views and inconsistent empirical findings reviewed are due in part to differences in the ages at which studies have assessed poverty effects (e.g., early, middle, or late childhood); outcomes such as cognitive development, socioemotional behavior, health, and educational attainment; data sources; and methodological approaches. However, they also can occur because of a limited understanding of the temporal dimensions of exposure to poverty (see Wagmiller et al. [2006] for a review of this issue).

The timing of exposure to poverty does not specify how the effects of poverty exposure during a certain age period can differ by poverty exposure during other age period. Among children experiencing early childhood poverty, some could remain in poverty throughout childhood. Likewise, among children experiencing late childhood poverty, some will not have experienced poverty during early childhood. Simply estimating the effects of early or late childhood poverty may produce biased results to the extent that timing effects are confounded by effects of the duration and sequencing of poverty.

Focusing on the duration of exposure to economic deprivation poses similar problems. Suppose a researcher finds that spending five years living in poverty lowers children's educational attainment. This finding can serve as evidence for duration effects of poverty. However, children living in poverty for five years are not a homogeneous group, as a five-year poverty spell could occur primarily in their early, middle, or late childhood years. Children also could fall into this group by experiencing poverty for five consecutive years or by frequently moving in and out of poverty. Therefore, duration-based approaches may not adequately address the potential that children with longer exposure to poverty differ by its timing and instability.

The sequencing of exposure to poverty is presumed to capture the directionality of changes in poverty status, that is, its unfolding patterns over time. But studies tend to classify age patterns of exposure to poverty on an ad hoc basis because numerous combinations are possible with longitudinal data on poverty status. For example, if poverty status is observed five times during respondents' childhood, there are up to 32 age-varying patterns of poverty ($2^5 = 32$) that differ by its timing, duration, and stability. Although categorizing these patterns is necessary for parsimony, it may be prone to subjective operationalizations.

In sum, given the confounding of one temporal dimension of exposure to poverty with other temporal dimensions, it is not tenable to assume that the timing, duration, stability, and sequencing of exposure to economic deprivation operate independently (McDonough, Sacker, and Wiggins 2005). Wagmiller et al. (2006) assess the temporal dimensions of poverty simultaneously by using period-based (i.e., calendar-year) trajectories of poverty. Their analysis of the Panel Study of Income Dynamics (PSID) data finds that compared to no poverty, persistent poverty and moving out of poverty lowers the odds of high school graduation but moving into poverty does not. This study analyzes a more recent data set by constructing age-based trajectories of poverty and further investigating the role of age-varying covariates in the relation between poverty trajectories and child educational attainment.

The Role of Age-Varying Factors in Exposure to Poverty

Another complication in research on childhood poverty is that many of its correlates, such as family structure, employment status, childbearing, and residential mobility, also vary with age. The life course perspective acknowledges that sequences of transitions and events define multiple, interlocking trajectories that vary in synchronization (Elder 1985, 1998). However, most studies have focused on age-*constant* characteristics as the determinants of age-dependent exposure to poverty. To understand the dynamic process by which families select into and out of poverty over time, it is crucial to recognize that childhood poverty trajectory may not only affect but also be affected by its age-*varying* covariates.

To fix ideas, Figure 1 presents how researchers analyze two waves of data to examine the hypothesized causal relationships between age-dependent exposure to poverty (P), age-varying covariates (C), and child educational attainment (O). As with observational studies, the model displayed in Figure 1 assumes that unobserved factors do not affect age-dependent exposure to poverty, conditional on observed factors, but allows them to affect age-varying covariates and child educational attainment ($U \rightarrow C_2$ and $U \rightarrow O$). The model then hypothesizes that (1) age-varying covariates function as both confounders and mediators of age-dependent exposure to poverty and therefore (2) age-dependent exposure to poverty has a direct as well as an indirect effect on child educational attainment. Obviously, no unobserved confounding is a strong assumption. If unobserved factors (e.g., mothers' mental health history) not only affect child educational attainment but also exposure to poverty (i.e., U$\rightarrow P$), any estimated effect of age-dependent exposure to poverty will be biased. As demonstrated, however, the presence of age-varying covariates creates an overlooked source of bias even under the assumption of no unobserved confounding.

Past research has adopted two approaches to estimate the effect of age-dependent exposure to poverty. One approach is to exclude age-varying covariates observed at the second wave (C_2), treating age-dependent varying exposure to poverty as the sole age-varying determinant of child educational attainment. This approach suggests that conditioning on C_2 may not be desirable, because it allows age-dependent exposure to poverty and age-varying covariates to jointly determine child educational attainment, thereby obscuring the effect of poverty trajectory (Blau 1999; Duncan et al. 1998). However, omitted variables bias can arise to the extent that age-varying covariates serve as confounders of the relationship between childhood poverty and child educational attainment ($C_2 \rightarrow P_2$ and $C_2 \rightarrow 0$).

The other approach is to include C_2 to mitigate the omitted variables bias. Then, conditioning on C_2 may induce two problems. It makes poverty status at the first wave affect child educational attainment not only through the direct pathway ($P_1 \rightarrow 0$) but also through the indirect

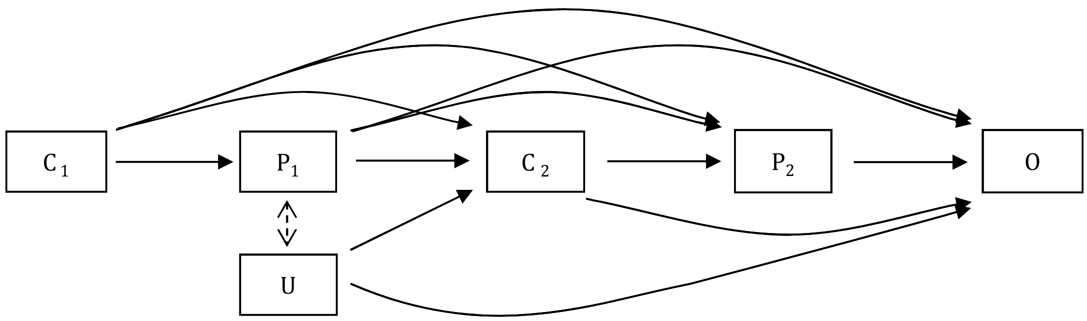

Figure 1: Conventional Pathways Linking Exposure to Poverty to Child Educational Attainment

Note: P = exposure to poverty, C = age-varying covariates, O = child educational attainment, and U = unobserved factors.

pathway ($P_1 \rightarrow C_2 \rightarrow 0$). As C_2 stands on the pathway from age-dependent exposure to poverty to child educational attainment, adjusting for C_2 as mediators of P_1 is likely to "control away" part of the effect of age-dependent exposure to poverty, leading to understating its effect. Conditioning on C_2 also creates a "collider" problem. Because C_2 has poverty status at the first wave and unobserved factors as its common causes ($P_1 \rightarrow C_2 \rightarrow U$), an unnecessary correlation between P_1 and U occurs (Pearl 2009). Given that the extent of this correlation is unknown, the direction of bias resulting from the collider problem is ambiguous; however, as unobserved factors also affect child educational attainment ($U \rightarrow 0$), it is clear that conditioning on age-varying covariates makes it difficult to distinguish the effect of age-dependent exposure to poverty from that of unobserved factors.

Thus, the previous approaches pose difficulties in addressing endogenous relationships between age-dependent exposure to poverty and age-varying covariates. Conventional regression models may be liable to bias as they either do condition on age-varying covariates to adjust for confounding or do not condition on them to avoid overcontrolling and collider stratification, but not both. While making the same assumption of no unobserved confounding of age-dependent exposure to poverty as in conventional approaches, the present study addresses how to handle another source of confounding that occurs owing to the presence of observed age-varying characteristics. Particularly, it evaluates whether observed age-varying covariates function primarily as confounders or mediators of poverty trajectories.

Racial/Ethnic Differences in Poverty Effects

A final consideration is concerned with population heterogeneity in poverty effects. Much research suggests that the impacts of exposure to poverty are less strong for nonwhites than for whites (Bolger et al. 1995; McLeod and Nonnemaker 2000). On one hand, compared to whites, racial/ethnic minority groups are more likely to experience structural disadvantage such as concentrated poverty, criminal victimization, low-quality schools, and limited social support systems (Wilson 1987). Faced with such structural disadvantage, they are often exposed to various forms of stressful life events that include family instability, poor health, and family conflict (Ellwood 1988). Furthermore, blacks and, to a lesser degree, Hispanics have more exposure to persistent poverty (Duncan and Rodgers 1988). Even if they move out of poverty, their income levels tend to be lower than those of whites, indicating that the disparity in socioeconomic resources by poverty status is less strong for nonwhites than for whites. On the other hand, poverty exposure may have more severe impacts on whites. As they have less exposure to structural disadvantage, experiencing poverty would be a more salient factor affecting child attainment. For example, white children are more likely to live in less disadvantaged neighborhoods, and as a result, social comparisons driven by differing poverty exposure may have more negative consequences (McLeod and Shanahan 1993).

Together, prior research provides plausible explanations for population heterogeneity in poverty effects. This study examines whether these explanations for the differential impacts of childhood poverty across racial/ethnic groups are borne out when accounting for interdependence among the temporal dimensions of poverty exposure and dynamic relationships between poverty exposure and its age-varying covariates.

Data and Methods

Data

Data come from the National Longitudinal Survey of Youth 1979 (NLSY79) and its mother–child supplement, the CNLSY. The NLSY79 is a longitudinal study of 12,686 men and women aged 14 to 21 in 1979, who have been interviewed annually until 1994 and biennially since then. It has collected rich information on respondents' family backgrounds, cognitive and socioemotional characteristics, educational attainment, fertility, family formation, and labor market experiences. In 1986, the NLSY79 was expanded to include the CNLSY, a biennial assessment of the children of NLSY79 mothers. All of a mother's children are eligible for the CNLSY. Starting in 1994, the CNLSY has interviewed children aged 15 and older using questionnaires similar to those of the NLSY79.

The analytic sample is based on 6,402 children who were born between 1981 and 1990 and who have been followed until age 20. Children born prior to 1981 are excluded because their birth could affect mothers' characteristics. Children born after 1990 are also excluded because their educational attainment at age 20 is unavailable in 2010, the latest survey year. To reflect the fact that the NLSY79 and the CNLSY have been conducted biennially since 1994 and 1986, respectively, the analytic sample is rearranged such that children are grouped into a series of adjacent birth cohorts (Han and Fox 2011). Children born in 1981 and 1982 are categorized together as the first cohort of the sample, with the other four cohorts of children grouped in the similar fashion (i.e., 1983–84, 1985–86, 1987–88, and 1989–90). This data structure aids in maximizing the sample size and following the sample children longitudinally.

The final analytic sample consists of 3,744 children who continued to participate in the CNSLY from birth to ages 15–16 and who reported their educational attainment at age 20.[1] This study employs a multiple imputation (MI) method to address item nonresponse (Little and Rubin 2002). MI uses observed data to replace missing values with multiple imputed data and then obtains estimates averaged over these complete data. Standard errors are calculated in a way to take into account the uncertainty about sampling and imputation model. Ten MI data are used to estimate the effect of poverty trajectories.[2]

Main Variables

The outcome variable is high school graduation status at age 20. Given that high school dropout rates are still substantial for low-income families, high school graduation is a key factor of the social stratification and mobility processes (National Center for Educational Statistics 2013). High school graduates include children who earned a General Educational Development (GED) diploma. In a sensitivity check, I treat GED holders as not graduating from high school because their later outcomes are reported to be more similar to those of high school dropouts (Cameron and Heckman 1993).

The main explanatory variable is children's poverty trajectory during childhood, which is based on family poverty status from birth to age 15 or 16. Poverty status in any given year is determined using the official poverty threshold set by the U.S. Census Bureau. The threshold is computed by adjusting total annual family income for family size and updated for inflation using the Consumer Price Index. Children are considered to be in poverty if their family's total

[1] Respondents who were lost to follow-up include both those who permanently dropped out of the survey and those who left the survey but rejoined later. The analysis addresses the issue of sample attrition in the propensity score weighting framework.

[2] The imputation model contains all analysis variables, but imputed values on the outcome are excluded in the analysis (Royston 2005).

income is below the official poverty threshold. The analysis also uses an alternative measure of poverty status in which the official poverty threshold is inflated by 25 percent to examine the link between trajectories of near-poverty and high school graduation.

Covariates

This study includes an extensive array of mother's age-constant covariates. Race/ethnicity is measured as black, Hispanic, and non-Hispanic white (reference). Educational attainment is constructed as three dummy variables for less than high school, high school (reference), and at least some college. The Armed Forces Qualification Test (AFQT) is a composite score derived from the Armed Services Vocational Aptitude Battery administered in 1980. It consists of a series of tests measuring knowledge and skill in areas such as mathematics and language. The AFQT has been extensively used to measure cognitive skills (Cawley et al. 2000). The Rotter's locus of control scale measures a degree of control individuals feel: individuals who believe that outcomes are due to luck have an external locus of control, whereas individuals who believe that outcomes are due to their own efforts have an internal locus of control. A 4-item abbreviated version of this scale, administered in 1979, generates a 4-point Likert scale ranging from 1 (*external*) to 4 (*internal*) for each item and sums the scores ($\alpha = 0.44$). The 10-item Rosenberg's self-esteem scale, administered in 1980, measures a degree of approval or disapproval toward oneself. I code each 4-point Likert scale item as 1 (*low*) to 4 (*high*) and sum the scores ($\alpha = 0.87$).

The analysis also includes a set of child's age-constant covariates. Child gender is coded 1 for female and 0 for male. Low–birth weight status is coded 1 if a child weighed less than 2,500 grams at birth and 0 if otherwise. Birth year is measured with a series of dummy variables with the year of 1981 as the reference year.

Table 1 reports descriptive statistics for age-constant characteristics. As documented elsewhere (Fomby and Cherlin 2007), children born in the 1980s in the CNLSY have mothers who were relatively younger at their first child's birth than mothers who were nationally representative in the U.S. population. The analytic sample, therefore, is drawn from less advantaged families. They are more likely to be minorities, have a low level of education, and have low–birth weight children.

For age-varying covariates, this study includes marital status, mother's employment status, number of children, region of residence, and urban residence. The age-varying covariates measured at birth are treated as baseline covariates, alongside the age-constant covariates described earlier. Marital status is coded 1 for married and 0 for not married. Mother's employment status is measured by three dummy variables for not working (reference), working part-time ($<$ 30 hours/week), and working full-time ($\geq$ 30 hours/week) in the past calendar year. The number of children is the total number of children in the focal child's household. Region of residence is measured as Northeast, North Central, South (reference), and West. Urban residence is coded 1 if a family lived in a county with 50 percent or more urban population and 0 if otherwise.

Table 2 presents descriptive statistics for age-varying characteristics. The percentage of children experiencing poverty steadily declined throughout childhood, from 33 percent at ages 1–2 to 29 percent at ages 7–8 to 24 percent at ages 15–16. The percentage of children living in a married-parent family declined from 68 percent at ages 1–2 to 60 percent at ages 15–16. Changes in mothers' employment status show that whereas a majority of mothers did not work or worked part-time in the first several years after birth (75 percent), a majority of mothers worked full-time during their children's late childhood years (55 percent). The number of children in the household increased over time. On average, a focal child had one sibling at ages 1–2, while having two siblings at ages 15–16. There were slight changes in residence by region over time, with a decrease in families living in the Northeast and an increase in families living in the South. A majority of families resided in urban areas, though more families moved from urban to rural areas as their children aged. These patterns indicate that a snapshot portrait of family contexts may not characterize adequately family contexts during the entire childhood period. Age-varying factors do not shift in the same direction, suggesting that they are likely to affect as well as be affected by one another.

Table 1: Descriptive Statistics for Age-Constant Characteristics ($N = 3,744$)

	Mean/%	S.D.	Min.	Max.
Outcome				
High school graduation, %	77.32			
Maternal characteristics				
Race/ethnicity, %				
Black	32.2			
Hispanic	22.22			
White	45.51			
Educational attainment, %				
Less than high school	24.52			
High school	47.17			
At least some college	28.31			
AFQT percentile score, mean	34.26	27.20	1	99
Locus of control, mean	11.06	2.43	4	16
Self-esteem, mean	21.68	4.16	9	30
Age at first birth, mean	21.65	3.71	13	33
Age at child's birth, mean	24.53	3.37	17	33
Child characteristics				
Female, %	48.85			
Low birthweight, %	10.84			
Birth year, %				
1981	11.67			
1982	12.10			
1983	11.81			
1984	9.05			
1985	11.75			
1986	8.07			
1987	10.12			
1988	7.61			
1989	11.00			
1990	6.81			

Analytic Strategy

This study first applies longitudinal latent class analysis (LCA) to evaluate the timing, duration, stability, and sequencing of exposure to poverty simultaneously (Jones and Nagin 2007; Muthén 2004). As a finite mixture modeling, LCA treats the data as a mixture of the unobserved groups of individuals, that is, latent classes, and identifies the smallest number of latent classes that best describe the associations among a set of observed indicators. Similar to Wagmiller et al.'s (2006) approach, this study uses LCA to find the best-fitting number of trajectories of childhood poverty. Because children's poverty experiences at each age serve as observed age-ordered indicators, these trajectories are distinct from one another in terms of the temporal dimensions of poverty exposure.[3]

[3]Latent class growth analysis (LCGA) was also considered to examine the dependence across exposure to poverty over time. LCGA identifies latent trajectory classes by estimating different growth curve factors, i.e., intercepts and slopes, across the classes (Muthén and Muthén 2000). LCA does not define the form of dependence, whereas LCGA assumes a certain functional form of the growth curve factors prior to fitting models. Therefore LCA allows for investigating at which age changes in poverty status likely occur in a more flexible manner. I also fitted linear LCGA models but found higher-order LCGA models to be unstable on several occasions. For these reasons, the analysis is based on LCA.

Table 2: Descriptive Statistics for Age-Varying Characteristics ($N = 3,744$)

	Ages 1–2	Ages 7–8	Ages 15–16
Poverty status, %	33.22	29.11	24.06
Marital status, %	67.55	62.18	60.15
Employment status, %			
Not working	36.73	31.22	21.98
Part-time	38.25	30.61	22.89
Full-time	25.03	38.17	55.13
Number of children, mean	1.95	2.69	3.01
Region, %			
Northeast	14.78	13.61	12.71
North Central	24.41	25.36	24.86
South	39.83	39.74	41.85
West	20.97	21.29	20.57
Urban residence, %	79.20	79.21	71.45

Let the latent variable C have J trajectory classes ($j = 1, 2, \ldots, J$) and P_k denote poverty status at age k ($k = 1, 2, \ldots, K$). Estimated trajectory class probabilities for child i are given by

$$Pr\left(C_i = j | P_1, P_2, \ldots, P_k\right) = \frac{Pr(C_i=j)Pr(P_1|C_i=j)Pr(P_2|C_i=j)\ldots Pr(P_K|C_i=j)}{Pr(P_1,P_2,\ldots,P_K)} \tag{1}$$

where $Pr(P_1, P_2, \ldots, P_K)$ is the joint probability of all P's. Note that each child can have fractional class membership. Following the literature on finite mixture modeling (Muthén 2004), the analysis estimates the probability of falling in trajectory class j of the latent variable C through multinomial logit regression with a vector of baseline covariates, $\boldsymbol{X}_0$:

$$\log\left[\frac{Pr(C = j)}{Pr(C = J)}\right] = \delta_j + \mathbf{X}_0\theta_j. \tag{2}$$

To select the best-fitting number of trajectories of childhood poverty, two statistical criteria, the Bayesian information criterion (BIC) and entropy, are used. More parsimonious and accurate models that fit the data tend to produce the lower BIC, whereas models that better differentiate among trajectory classes tend to produce the higher entropy (Celeux and Soromenho 1996; Raftery 1996). The analysis also utilizes the substantive knowledge gained from past research about age-dependent exposure to poverty for model selection, attending to the shape and proportion of each trajectory class.

Next, this study employs propensity score weighting to directly address how to estimate the effect of poverty trajectories when age-varying covariates are present. This approach uses an inverse probability of treatment (IPT) weighting estimator (Hernán, Brumback, and Robins 2000). For child i, the IPT weighting calculates the conditional probability of exposure to poverty at age k as propensity score, ps child's propensity score. On one hand, children exposed to poverty at age k are given a weight of $1/ps$, thereby assigning those with the higher propensity scores lower weights while those with the lower propensity scores have higher weights. On the other hand, children not exposed to poverty at age k are given a weight of $1/(1ps)$, thereby assigning those with the higher propensity scores higher weights while those with the lower propensity scores have lower weights. As a result, children who experience poverty and children who do not at age k are balanced on prior poverty history and observed age-constant and age-varying covariates.

Let P_{ik} denote poverty status at age k and X_{i0}be a vector of baseline covariates, as defined earlier. For age-varying covariates, overbars denote covariate history up to age $k : \bar{X}_{ik} = \{\mathbf{X}_{i0}, \mathbf{X}_{i1}, \ldots, \mathbf{X}_{ik}\}$. The IPT weights are given by

$$w_i = \prod_{k=1}^{K} \frac{1}{Pr(P_{ik}|\bar{P}_{ik-1}, \mathbf{X}_{i0}, \bar{X}_{ik-1})}, \tag{3}$$

where Π is the product operator and the denominator is the probability that child i received the

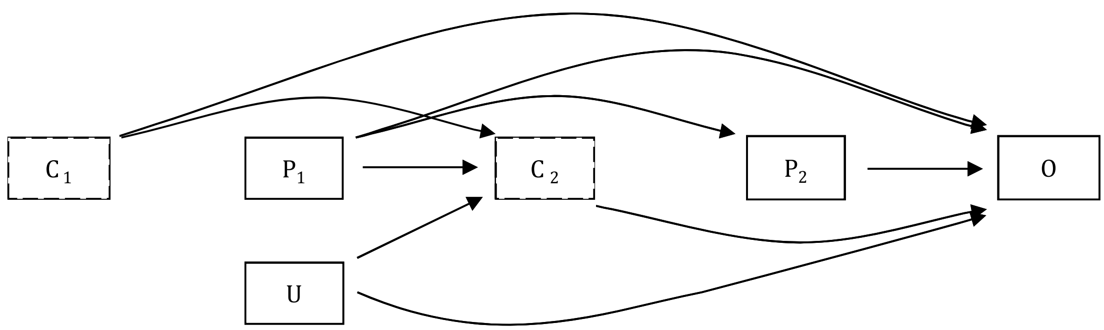

Figure 2: Propensity Score Weighted Pathways Linking Exposure to Poverty to Child Educational Attainment

Note: P = exposure to poverty, C = age-varying covariates, O = child educational attainment, and U = unobserved factors.

child's actual poverty status at age k, conditional on prior poverty history and age-constant and age-varying covariates. A pooled logit regression model is fitted to estimate the IPT weights, in which age-dependent exposure to poverty is a function of poverty status measured at age $k-1$, baseline covariates, and age-varying covariates measured at age $k-1$. Experimenting with alternative model specifications indicated that the results presented here are robust to using age-varying covariates measured at age k and interactions between race/ethnicity and other covariates (results available on request). The IPT weights constructed previously, however, are known to have larger variance, as a small number of observations with extreme weights tend to dominate the estimation process (Hernán, Brumback, and Robins 2002). To increase efficiency, I compute stabilized IPT weights:

$$sw_i = \prod_{k=1}^{K} \frac{Pr(P_{ik}|\bar{P}_{ik-1},\mathbf{X}_{i0})}{Pr(P_{ik}|\bar{P}_{ik-1},\mathbf{X}_{i0},\bar{X}_{ik-1})}, \qquad (4)$$

where the numerator is the probability that child i received the child's actual poverty status at age k, conditional on prior poverty history and baseline covariates (see Table A1 in the online supplement).

Figure 2 displays how the IPT weighting modifies the pathways linking age-dependent exposure to poverty and child educational attainment seen in Figure 1. Since adjusting for observed age-varying covariates as confounders are made in the IPT weights, age-dependent poverty status is independent of these covariates, and thus the pathways from C_1 to P_1, C_1 to P_2, and C_2 to P2 can be removed. The removal of these pathways resolves over-controlling because it is no longer necessary to condition on age-varying covariates as mediators in estimating the effect of age-dependent exposure to poverty. Also, the IPT weighting avoids another source of unobserved heterogeneity that arises due to the collider problem. As conditioning on age-varying covariates is not necessary, unobserved factors (U) affecting those covariates have no connection to age-dependent exposure to poverty.

Recall that, as in conventional regression models, the propensity score weighting approach identifies the effect of poverty trajectory assuming that no unobserved factors affect age-varying exposure to poverty conditional on observed factors (Robins 1999). To the extent that this assumption is violated, estimates from both approaches are likely to be biased. However, conventional regression models must make an additional assumption that observed age-varying covariates function as either exogenous factors or confounders of age-dependent exposure to poverty. As shown in Figure 2, the IPT weighting relaxes this assumption by generating a pseudo-population in which exposure to poverty is sequentially independent of prior observed covariates.

Sample attrition is inevitable in longitudinal data sets. To the extent that there is nonrandom

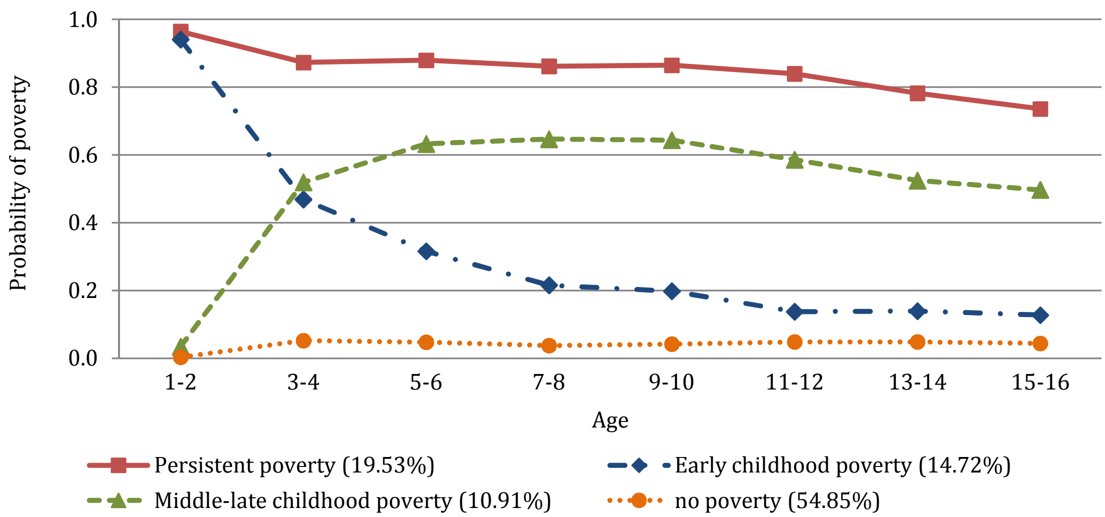

Figure 3: Trajectories of Exposure to Poverty during Childhood

attrition, any analysis will produce biased results. The analysis addresses this issue by constructing weights for age-dependent exposure to censoring (Robins et al. 2000). I calculate the conditional probability of remaining in the analytic sample at age k for child i and weight each child by the inverse of that probability. Let $L_{ik} = 1$ if child i was lost to follow-up by age k and $L_{ik} = 0$ otherwise, and let $\bar{L}_{ik-1}$ = indicate that child i was not lost to follow-up by age $k-1$. The stabilized censoring weights are given by

$$cw_i = \prod_{k=1}^{K} \frac{Pr(L_{ik}=0|\bar{L}_{ik-1}=0,\bar{P}_{k-1},\mathbf{X}_{i0})}{Pr(L_{ik}=0|\bar{L}_{ik-1}=0,\bar{P}_{k-1},\mathbf{X}_{i0},\bar{X}_{ik-1})}. \quad (5)$$

This study estimates the effect of poverty trajectories on high school graduation with the product of the stabilized IPT weights and the stabilized censoring weights as final weights ($fw_i = sw =_i \times cw_i$), fitting a logit model:

$$\log\left[\frac{\Pr(O=1)}{1-\Pr(O=1)}\right]_{fw} = \alpha + \beta C + \mathbf{X}_0\gamma \quad (6)$$

where O denotes high school graduation and C is the indicator of trajectories of poverty during childhood. The model controls for baseline covariates because these factors enter into both the numerator and denominator of the stabilized weights. Robust standard errors are computed to correct for the clustering of siblings within families and for within-individual correlation in the weighted sample (Robins et al. 2000). In the analysis, the propensity score weighting models are contrasted with two conventional regression models. One model is estimated with adjustment for baseline covariates only, while the other is estimated with adjustment for baseline covariates as well as age-varying covariates averaged over ages 1–2 to 15–16 years. Both models are estimated with the censoring weights but without the IPT weights.

Results

Trajectories of Exposure to Poverty

Results from the longitudinal LCA appear in Figure 3. The LCA identifies four trajectories of children's exposure to poverty. As shown in Table A2 in the online supplement, the four-class model provides a better fit in terms of BIC (a reduction by 668) and has little difference in terms of entropy (0.91 vs. 0.92) than the three-class model. While the five-class model makes a small improvement on the four-class model on the basis of BIC (a reduction by 76), adding one more class exacerbates entropy (from 0.91 to 0.84). Given these results, the analysis opts for the four-class model as best representing the

Table 3: Stabilized Inverse Probability of Treatment (IPT), Censoring, and Final Weights

			Percentile				
Weight	Mean	S.D.	1st	25th	Median	75th	99th
Stabilized IPT weight (sw)	0.99	0.53	0.18	0.70	0.94	1.10	3.53
Stabilized censoring weight (cw)	1.00	0.08	0.85	0.96	0.99	1.02	1.29
Final stabilized weight ($sw \times cw$)	0.99	0.54	0.19	0.70	0.92	1.10	3.54

data and differentiating children in terms of their poverty trajectories.

Figure 3 displays the estimated probability of exposure to poverty by age. Inspection of these probabilities indicates that children are classified into one of the four trajectory classes: persistent poverty, early childhood poverty, middle-late childhood poverty, and no poverty.[4] The persistent poverty group accounts for 19.5 percent of children and is most likely to experience economic disadvantage throughout childhood. Although they gradually move out of poverty over time, their probability of exposure to poverty never falls below 0.7. The early childhood poverty group comprises 14.7 percent of children, whose level of exposure to economic deprivation is high in early childhood but declines by middle childhood. They have a low chance of being exposed to poverty in late childhood, with the estimated probability of less than 0.2. By contrast, the middle-to-late childhood poverty group (10.9 percent) experiences a rapid increase in the risk of exposure to poverty in early childhood. Though their risk of exposure to poverty is lower than that for children in the persistent poverty group and declines during late childhood, they are likely to remain in poverty. After they reach school age, their probability of living in poverty is at least 0.5. The no-poverty group accounts for 54.9 percent of children and has the least chance to experience economic deprivation throughout childhood. Their probability of exposure to poverty changes little and is always less than 0.1.[5]

Figure 3 reveals two notable features of poverty trajectories. First, changes in poverty status occur mostly during early to middle childhood. This finding highlights the importance of specifying the timing of exposure to poverty in examining how changes in poverty status are sequenced. Second, middle-to-late childhood poverty has more sustained exposure to economic deprivation than early childhood poverty. These two groups differ from each other not only in terms of the timing of exposure to poverty but also in terms of its duration. Both features help interpreting the effect of poverty trajectories on high school graduation.[6]

Propensity Score Weights

Table 3 presents descriptive statistics for stabilized IPT weights, censoring weights, and final weights. If the propensity score weighting models are correctly specified, in expectation, the distribution of these weights should be centered around values close to 1, have small variance, and be symmetric (Hernán et al. 2000). All three weights meet these conditions. The stabilized IPT weights have a mean of 0.99 and a standard deviation of 0.53 and are only slightly skewed to the right, whereas the censoring weights have a mean of 1 and a standard deviation of 0.08 and

[4] I initially expected to identify intermittent poverty as another trajectory (Moore et al. 2002). However, children in the fifth trajectory class identified by the five-class model have the probability of poverty exposure ranging from 0.1 to 0.2, paralleling with those experiencing no poverty. This suggests that the fifth trajectory class cannot be categorized as intermittent poverty. A supplemental analysis employs an alternative way to identify children experiencing intermittent poverty and reestimates the effect of poverty trajectories on high school graduation.

[5] The multinomial logit model (Table A3 in the online supplement) shows that children experiencing poverty over any extended time period are less advantaged than children experiencing no poverty in terms of a number of family background characteristics.

[6] Because of these features, the four trajectory classes identified here differ from Wagmiller et al.'s (2006), where trajectories representing changes in poverty status are more gradual.

Table 4: Effect of Poverty Trajectories on High School Graduation

	Model 1	Model 2	Model 3
(1) Persistent poverty	$-1.08^{\dagger}$	$-0.92^{\dagger}$	$-1.45^{\dagger}$
	(0.28)	(0.30)	(0.33)
(2) Early childhood poverty	-0.49^{*}	-0.46^{*}	$-0.79^{\dagger}$
	(0.26)	(0.26)	(0.30)
(3) Middle-late childhood poverty	$-0.64^{\dagger}$	$-0.52^{\dagger}$	$-0.86^{\dagger}$
	(0.15)	(0.17)	(0.18)
(4) No poverty (reference)	—	—	—
Test of equality			
(1) vs. (2)	$p = 0.000$	$p = 0.009$	$p = 0.001$
(1) vs. (3)	$p = 0.108$	$p = 0.135$	$p = 0.064$
(2) vs. (3)	$p = 0.549$	$p = 0.825$	$p = 0.839$

Notes: Robust standard errors in parentheses. Model 1 is estimated with baseline covariates only, Model 2 with both baseline and age-varying covariates, and Model 3 with propensity score weights. All models are estimated with censoring weights.
* $p < 0.10$; † $p < 0.05$ (two-tailed tests).

are normally distributed. The final weights also have similar properties.[7]

Multivariate Results

Table 4 reports estimates for the effect of poverty trajectories on high school graduation. Parameter estimates from all models are based on the assumption of no unobserved confounding. Model 1 is estimated with only baseline covariates, model 2 with both baseline and age-varying covariates. Model 3 is estimated with propensity score weights to examine observed age-varying confounding.[8] Model 1 shows that, compared to no poverty, persistent poverty is strongly negatively associated with high school graduation ($\beta = -1.08$, $p < 0.001$), reducing the odds by 66 percent ($\exp(-1.08) = 0.34$). The impact of early childhood poverty lowers the odds of high school graduation by 39 percent, whereas that of middle-to-late childhood poverty lowers the odds by 47 percent. Model 2 shows that the estimates are similar to, but smaller in magnitude than, those in model 1. Model 2 is problematic because it includes naive controls for age-varying covariates, thereby biasing estimates of the total impact of poverty trajectories.

The estimates from propensity score weighting (model 3) indicate the substantial and significant impact of poverty trajectories. Compared to no poverty, persistent, early, and middle-to-late childhood exposures to poverty reduce the odds of graduating from high school by 77 percent ($\exp(-1.45) = 0.23$), 55 percent, and 58 percent, respectively. The test of equality of coefficients shows that early and middle-to-late exposures to poverty do not differ in their impact ($p = 0.839$). However, children experiencing early childhood poverty are more likely than children experiencing persistent poverty to graduate from high school ($p = 0.001$), whereas children experiencing middle-to-late childhood poverty are only marginally so ($p = 0.064$).

In sum, the results show that any sustained exposure to poverty has an adverse impact on high school graduation even after age-varying covariates are properly accounted for. Given the greater impact found in the propensity score weighted model than in the model that mixes age-varying covariates as both confounders and mediators, age-varying covariates likely function as mediators rather than confounders of the association between poverty trajectories and high school graduation. Also, while statistically in-

[7]Weights are truncated at the 1st and 99th percentiles to avert disproportionate influence from outlying observations (Cole and Hernán 2008).

[8]See Table A4 for propensity score weighted estimates for the effects of baseline covariates on high school graduation.

Table 5: Effect of Poverty Trajectories on High School Graduation, by Race/Ethnicity

	Black ($n = 1,208$)	Hispanic ($n = 832$)	White ($n = 1,704$)
(1) Persistent poverty	-1.34^{*a}	$-1.44^{\dagger}$	$-1.84^{\dagger}$
	(0.69)	(0.55)	(0.63)
(2) Early childhood poverty	-0.53^{a}	-0.49^{a}	$-1.38^{\dagger}$
	(0.63)	(0.57)	(0.57)
(3) Middle-late childhood poverty	-0.45^{a}	$-1.13^{\dagger}$	$-0.98^{\dagger}$
	(0.37)	(0.35)	(0.28)
(4) No poverty (reference)	—	—	—
Test of equality			
(1) vs. (2)	$p = 0.008$	$p = 0.015$	$p = 0.171$
(1) vs. (3)	$p = 0.243$	$p = 0.582$	$p = 0.157$
(2) vs. (3)	$p = 0.098$	$p = 0.298$	$p = 0.475$

Notes: Robust standard errors in parentheses. All models are estimated with propensity score weights.
[a] indicates significant difference with whites at the 0.05 level.
* $p < 0.10$; † $p < 0.05$ (two-tailed tests).

distinguishable, children experiencing middle-to-late childhood poverty have slightly lower odds of high school graduation than children experiencing early childhood poverty, suggesting that the impact of middle-to-late childhood poverty is a combination of more recent and longer exposure to poverty.

To examine population heterogeneity in the effect of poverty trajectories, I take the same analytic approach, separately by race/ethnicity.[9] Table 5 reports propensity score weighted estimates by race/ethnicity. Among blacks, high school graduation rates are substantially lower only for children experiencing persistent poverty at the 0.10 level. Among Hispanics, high school graduation is significantly less likely for children experiencing persistent poverty and children experiencing middle-to-late childhood poverty but not for children experiencing early childhood poverty. Among whites, high school graduation rates are substantially and significantly lower for all children experiencing any extended exposures to poverty than for children experiencing no poverty.

Therefore a clear pattern emerges in which the impact of poverty trajectories is strongest among whites, followed by Hispanics and then by blacks. While the impact differs significantly between whites and blacks, only early childhood poverty has the differential impacts between whites and Hispanics. Persistent poverty ubiquitously lowers the likelihood of high school graduation, but the impacts of other poverty trajectories vary across racial/ethnic groups. For blacks and Hispanics, early childhood poverty is associated with higher rates of high school graduation than experiencing persistent poverty ($p = 0.008$ and $p = 0.015$, respectively). For whites, however, early childhood poverty exerts an adverse influence on high school graduation that is comparable to persistent poverty ($p = 0.171$), suggesting its lingering impact. Middle-to-late childhood poverty lowers the odds of high school graduation for Hispanics and whites but not for blacks. Therefore an improvement in economic condition during either early or middle-to-late childhood benefits children's educational attainment for blacks, whereas it does so for Hispanics only if it occurs during middle-to-late childhood. For whites, any sustained exposure to poverty puts children at risk of lower educational attainment, even if they ex-

[9]Similar to the main analysis, the subgroup analysis indicates that propensity score weighted estimates are stronger in magnitude and significance than those from the model that include age-varying covariates (results available on request).

Table 6: Effect of Poverty Trajectories on High School Graduation

	Model 1	Model 2	Model 3	Model 4
Persistent poverty	$-1.41^{\dagger}$	$-1.38^{\dagger}$	$-1.08^{\dagger}$	$-0.98^{\dagger}$
	(0.32)	(0.27)	(0.28)	(0.32)
Early childhood poverty	$-0.93^{\dagger}$	$-0.69^{\dagger}$	-0.49^{*}	-0.13
	(0.29)	(0.26)	(0.28)	(0.26)
Middle-late childhood poverty	$-0.78^{\dagger}$	$-0.94^{\dagger}$	$-0.63^{\dagger}$	$-0.85^{\dagger}$
	(0.18)	(0.21)	(0.18)	(0.30)
Intermittent poverty		-0.53		
		(0.23)		
No poverty (reference)	—	—	—	—

Notes: Robust standard errors in parentheses. Models 1 to 3 are estimated with propensity score weights, while Model 4 with cousin fixed-effects. In Model 1, GED holders are treated as high school dropouts. In Model 2, children are treated as experiencing intermittent poverty if changes in their poverty status occurred at least four times from birth to ages 15–16, regardless of their latent class membership. In Model 3, near-poverty status is coded 1 if below 125 percent of the official poverty threshold and 0 if otherwise. Model 4 is estimated based on 1,153 children born to 383 mothers who are sisters.
* $p < 0.10$; † $p < 0.05$ (two-tailed tests).

perience an improvement in economic condition during some periods of childhood.

Supplemental Analyses

The analysis has so far treated GED recipients as high school graduates, estimated the four poverty trajectory class model, defined poverty status by the official poverty threshold, and assumed no unobserved confounding. Several models are estimated to supplement the main findings (Table 6). Classifying GED recipients as high school dropouts (model 1) does not alter the main results, suggesting the robustness of the findings to alternative ways to categorize GED recipients.

In model 2, children moving in and out of poverty at least four times during childhood are classified as experiencing intermittent poverty (9 percent of the sample children). Among these children, 26 percent had been classified as persistently poor, 21 percent as poor in early childhood, 40 percent as poor in middle-to-late childhood, and 13 percent as nonpoor. Compared to no poverty, intermittent poverty is negatively associated with high school graduation, with its impact smaller than that of other poverty trajectories.

Model 3 estimates the impact of poverty trajectories based on near-poverty, defined as living below 125 percent of the official poverty threshold. Compared to no near-poverty, persistent exposure to near-poverty lowers the odds of graduating from high school, followed by middle-to-late and early childhood exposures to near-poverty. Although these estimates are smaller than the estimates based on the official poverty threshold, the results are generally well aligned with those from Table 4.

Model 4 uses a cousin fixed-effects model by exploiting the research design of the CNLSY that traces children whose mothers are sisters. Because of shared family and neighborhood characteristics among these mothers while growing up, comparing the outcome between cousins is expected to eliminate selection bias arising from unobserved maternal family background (Geronimus Korenman, and Hillemeier 1994). Cousin differences in poverty experience during childhood then can be attributed to a causal effect of poverty trajectories. Results are consistent with the main findings, with the exception that the effect of early childhood poverty is smaller and insignificant (but in the same direction).[10]

[10]The estimates from the cousin fixed-effects model should be interpreted with caution. They are based on a smaller sample of children whose mothers are sisters but differ by their poverty trajectory (1,153 vs. 3,744),

Table 7: Effect of Poverty on High School Graduation

Specification		
Snapshot measures		
A. Poverty at ages 1-2	-0.40^{*}	(0.20)
B. Poverty at ages 9-10	$-0.32^{\dagger}$	(0.12)
C. Poverty at ages 15-16	$-0.43^{\dagger}$	(0.11)
Temporal measures		
D. Timing		
Ages 0-4	$-0.42^{\dagger}$	(0.15)
Ages 5-10	-0.15	(0.14)
Ages 11-16	$-0.46^{\dagger}$	(0.13)
E. Duration (percent of years in poverty)	$-0.01^{\dagger}$	(0.00)
F. Instability		
Number of changes in poverty status	$-0.10^{\dagger}$	(0.04)
Poverty at all ages	$-0.76^{\dagger}$	(0.19)
G. Sequencing (ages 0-8 vs. ages 9-16)		
Persistent poverty	$-0.82^{\dagger}$	(0.14)
Moving out of poverty	$-0.46^{\dagger}$	(0.14)
Moving into poverty	-0.34	(0.25)
No poverty (reference)		

Note: Robust standard errors in parentheses. All models control for baseline covariates (not shown) and are estimated with censoring weights. For sequencing, children are treated as experiencing poverty if they did so at least half the time either during early (ages 0-8) or late (ages 9-16) childhood. * $p < 0.10$; † $p < 0.05$ (two-tailed tests).

For the purpose of comparison to the main findings, I also estimate conventional regression models using various snapshot and temporal measures of childhood poverty (Table 7). Each model includes only one measure of childhood poverty and is estimated with control for baseline covariates but also with the censoring weights. To simplify matters, poverty status at ages 1–2 (A), 9–10 (B), or 15–16 (C) is selected as one of the snapshot measures. The estimates are smaller than those from the preferred model (model 3, Table 4), highlighting the utility of longitudinal measures of childhood poverty against cross-sectional measures (Duncan and Brooks-Gunn 1997).

The timing-based estimates (D) show that middle (ages 5–10) childhood poverty has little impact after accounting for early (0–4) and late (11–16) childhood poverty, which is inconsistent with the finding that suggests the important role of middle childhood poverty as it is likely to lead children to remain in poverty through late childhood. The duration- and instability-based estimates (E and F) are consistent with the findings, pointing to the adverse impacts of a sustained exposure to poverty and frequent changes in poverty status, respectively. The sequencing-based estimates (G) show little impact of moving into poverty, which is contrary to the finding.[11] Although the discrepancies found for the timing and sequencing of poverty exposure might not be overly large, the results in Table 7 nonetheless provide a cautionary note on conventional approaches that consider only the limited set of the

raising a concern about external validity. Furthermore, the cousin fixed-effects model is limited in accounting for within-family heterogeneity. Despite growing up in the same household, sisters are likely to differ by their upbringing, socioeconomic attainment, and family formation in unmeasured ways.

[11] In the sequencing model, children moving out of poverty and children moving into poverty are mutually exclusive, whereas in the timing model, children experiencing early poverty and children experiencing late poverty are likely to overlap because some children who experience early poverty can remain in poverty through late childhood.

temporal dimensions of childhood poverty and overlook the role of its age-varying covariates.

Discussion

How childhood poverty exerts short-term and long-term influences on child attainment has become a pressing issue, as children have been the poorest age group in U.S. society (Shonkoff and Phillips 2000). However, such aggregate portraits of childhood poverty obscure considerable flux in the economic circumstances of children (Aber et al. 2006; Duncan and Brooks-Gunn 1997). Some children may grow up in poverty throughout childhood, others may live in poverty only at earlier ages, and still others may fall into poverty at later ages. Furthermore, changes and nonchanges in poverty status do not occur in a vacuum. Age-dependent exposure to poverty may shape and be shaped by other age-varying factors. These aspects of childhood poverty point to the need to address interdependence among the timing, duration, stability, and sequencing of exposure to economic deprivation (Wagmiller et al. 2006) and, at the same time, dynamic relationships between exposure to poverty and other factors over time (Caspi et al. 1989; Cunha and Heckman 2007). Taking these revised temporal perspectives on childhood poverty, the present study identifies distinct trajectories of poverty during childhood, estimates their impact on high school graduation with appropriate adjustment for observed age-varying covariates, and investigates population heterogeneity in their impact.

The major finding of this study is that the impact of poverty trajectories on high school graduation is fairly insensitive to observed age-varying confounders. Given the concern that age-varying covariates pose a potential threat to inferring the effects of childhood poverty, any estimates would remain less obvious until they are tested against age-varying confounding. The results from the propensity score weighting model find the still strong impact of poverty trajectories, compared to the model that compounds age-varying covariates as both confounders and mediators. The finding indicates that individual- and family-level age-varying correlates function as mediators rather than confounders of the link between poverty trajectories and high school graduation, as age-dependent poverty status is more likely to affect, rather than be affected by, its age-varying covariates. This finding is reassuring regarding the preponderant role of childhood poverty in child educational attainment.

The analysis also finds that the duration of exposure to poverty constitutes a principal dimension of the effect of poverty trajectories. Even accounting for the timing, instability, and sequencing of poverty exposure does not alter the finding that experiencing poverty over an extended period of time during childhood substantially reduces children's educational attainment. The results also lend support to the claim that early childhood is a critical period for child development: children exposed to poverty during early childhood often experience persistent poverty; changes in poverty status are more likely to occur during early to middle childhood; and the impacts of early childhood poverty linger even among children moving out of poverty. However, later phases in childhood are equally consequential to child educational attainment, given the deleterious impact of middle-to-late childhood poverty. Children experiencing this trajectory suffer from more recent and sustained exposure to poverty. This finding differs from that of Wagmiller et al.'s (2006), implying that economic constraints on secondary education are greater for the cohort drawn from the CNLSY (born in the 1980s) than that from their PSID data (born in the late 1960s).

The results are consistent with the cumulative disadvantage perspective on childhood poverty, as persistent and middle-to-late childhood exposures to poverty clearly represent the process in which the early onset of poverty reinforces subsequent exposure to poverty during later periods in childhood (Caspi et al. 1989; Elder 1998). This should not downplay the unique role of early childhood poverty, however, given its long-run impact even without later exposure to poverty. The views on early versus late childhood poverty thus can be complementary rather than incompatible: early and late investment in children should be of equal importance.

Another important finding is that poverty trajectories have differential impacts by race/ethnicity. Their impact is most pronounced for whites, as any types of sustained exposure to economic deprivation lower their high school graduation rates. For other racial/ethnic groups, persistent poverty for blacks and Hispanics and middle-to-late childhood poverty for Hispanics are adversely associated with high school graduation. The deleterious impact of early childhood poverty lingers for whites, whereas it dissipates over time for blacks and Hispanics. The findings suggest that concentrated poverty among blacks and, to a lesser degree, Hispanics tends to dampen within-group poverty effects while sharpening between-group poverty effects (Corcoran 1995; Wilson 1987). The less strong impact of poverty trajectories among racial/ethnic minority groups also may reflect their adaptation to economic disadvantage through early family formation and extended social support (Hashima and Amato 1994; McLoyd et al. 2000). Taken together, these results call more attention to the extent to and ways in which poverty effects are heterogeneous across population subgroups.

Although this study extends the extant literature on childhood poverty in important ways, it is not without limitations. Most noteworthy is unobserved heterogeneity that may make the link between poverty trajectories and child educational attainment spurious. To reduce this concern, the analysis includes a rich array of age-constant and age-varying covariates in propensity score weighting models and uses a cousin-fixed effects model. Yet more efforts on identifying exogenous sources of variation in age-varying exposure to poverty are needed to facilitate causal inference. Next, the utility of finite mixture modeling warrants a caution. While the LCA model identifies the poverty trajectory groups that are a best fit to the data according to fit indices, it may run the risk of reifying those trajectory groups given the possibility of within-group heterogeneity (Bauer and Curran 2003; Sampson and Laub 2003). Finite mixture modeling should be taken as a stylized approximation of poverty trajectories that have a solid theoretical footing (Nagin and Tremblay 2005). Another limitation is that this study constructs poverty trajectories relying on the official poverty status. The supplemental poverty measure (SPM) provides an alternative poverty threshold that makes a number of adjustments, such as different family types, geographical differences, in-kind benefits, and income and payroll taxes (Short 2011). It is an emerging topic for future research to examine similarities and differences between longitudinal measures based on the official poverty threshold and those based on the SPM.

In closing, this article provides an updated temporal insight on childhood poverty by taking its temporal dimensions as a whole and accounting for its reciprocal relationships with other age-varying factors. This holistic approach has broader implications for research on parental and public investment in children. First, though not definitive, the results suggest a more balanced, long-term approach to allocating public and private resources across children's developmental stages to improve their educational attainment. Second, in so doing, it is crucial to attend to population heterogeneity that can differentiate the effect of childhood poverty across subgroups. Third, the findings are credible only to the extent that observed factors account sufficiently for selection into and out of poverty over time. While the assumption of no unobserved confounding is not likely to meet the conditions for causal inference, this study highlights another dimension of confounding. As confounding can occur because of time-varying and time-constant factors, equal attention should be paid to both types of confounding when estimating the effect of time-varying treatment. Finally, despite the substantial impact of poverty trajectories even after accounting for observed age-varying confounders, little is known about whether this finding holds true for trajectories of alternative economic measures (e.g., wealth) and other parental factors (e.g., family structure, employment, health, and parenting). Addressing how trajectories of various parental factors interact with one another is a key to understanding temporal patterns of parental investment in children.

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