The Temporal Dynamics of Generational Inequality

by

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DEDICATION

"The rising tide raises all boats."

To my friends and family, I could not have accomplished this without you. My love and appreciation are boundless.

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As I reflect on my time at Michigan, I can confidently say that my life has been made richer, with friends and loved ones, since I first started my PhD.

Nevertheless, graduate school can also be incredibly taxing. And I should know; I was in graduate school for *nearly* a decade! (Sometimes, at parties, I will shock people by telling them that my time at Michigan has spanned four presidential administrations, and the looks of horror never disappoint.)

But, despite a global pandemic, and enough sociopolitical events to fuel inequality research for years to come, my time in Ann Arbor has been among the best years of my life—thanks to my community of friends and colleagues.

Many people will know how much I love reading other people's dissertation acknowledgments. (And if you're reading these words right now, then this might be the case for you, too.) The exercise can be illuminating. It is one of the few times that academics write autobiographically—where scholars reveal the many unseen contributions of their family and friends. However, this is *also* the first time that I have really, truly appreciated why celebrities give such long and boring speeches at award shows, rattling off a list of people who helped them along the way. Of course, I realize that it is impossible for me to thank everyone who has ever supported me during my PhD. But, nevertheless, I persist.

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ABSTRACT

Time is a key component of social inequality and its consequences. It is not just *what* happens to you that matters, but *when* something occurs and *how long* it lasts. Decades of studies have shown that the consequences of inequality are shaped by the length and timing of exposure. My dissertation project builds on this research by investigating how these individual-level dynamics contribute to larger social processes. Drawing on two empirical cases—intergenerational poverty and wealth inequality—I advance our understanding of how population-level inequalities are shaped by different aspects of temporal dynamics, including life-course timing and shifting historical contexts.

Theoretically, I argue that systematic differences in year-to-year temporal dynamics are fundamental for explaining how a society becomes economically and racially stratified. To address the different facets of this argument, I developed three empirical studies to explore how temporal dynamics accumulate into long-term generational inequalities.

In my first study, I investigate why early-childhood disadvantage is associated with worse socioeconomic outcomes than later-childhood disadvantage. A dominant perspective in the social sciences holds that the consequences of disadvantage are uniquely harmful for young children during the earliest stages of development. Yet, an alternative explanation could be that these timing associations are explained by systematic differences in children's cumulative exposure to disadvantage. I test these two explanations in the context of childhood poverty. Contrary to a central claim in the study of poverty, I find no evidence for the dominant explanation. Comparing children who spend the exact same number of years in poverty, I show that differences in children's age-specific exposures to poverty fail to explain variation in adult income. Instead, I present evidence that these associations with poverty timing are better explained by

children's cumulative exposures. That is, when children are exposed to poverty at younger ages, they experience poverty for a larger share of childhood. This phenomenon—which I refer to as the cumulative dimension of timing—is evident in the case of poverty, but it can apply to any empirical context in which researchers find timing differences that are correlated with cumulative exposure.

In my second study, I examine a childhood-based explanation for why Black-White inequalities remain so persistent over time, despite historical fluctuations and antipoverty efforts. Given the importance of children's cumulative exposures to disadvantage, I estimate how much of the total Black-White difference in adult income can be explained by inequalities in children's poverty experiences. First, I present evidence of racial/ethnic inequalities in childhood poverty that are far more extreme than we previously realized, using traditional measures. Second, by jointly estimating the associations with children's rates and cumulative exposures to poverty, I show that temporal exposures offer a key explanation for the durable nature of racial/ethnic inequalities in America.

In my third study, I evaluate how the intergenerational basis for wealth inequality has shifted over the last three decades. By examining trends in total assets, at age 35, I find that changes to family origins have reduced inequalities between Black and White individuals. However, within-cohort analyses reveal that socioeconomic background continues to remain the largest contributor to the Black-White wealth gap, regardless of decade.

Taken together, my research illuminates the process by which an exposure to inequality becomes a pattern of inequality—and how these patterns of inequality become stratified social systems that persist across generations of families.

CHAPTER 1

Introduction

Many economic and racial inequalities remain persistent across generations, even though Americans are experiencing rising levels of volatility and instability, over their lifetimes. I resolve this tension by investigating how the temporal dynamics of people's lives work to produce (and reproduce) social inequalities.

In many contexts, an exposure to inequality is more damaging when a person experiences an unequal condition for a longer period of time—or during a crucial period of timing. This project is motivated by this one single fact. Whether or not a person experiences an inequality is *only one* dimension by which social hierarchies form and persist over time. I argue that temporal exposures are *essential* for explaining how an inequality "takes effect" and produces harm.

Each chapter of my dissertation is part of a larger intellectual project that seeks to establish the foundational role of temporal dynamics for explaining society's most rigid inequalities that persist across generations.

1.1 Why Generational Inequality?

At its philosophical foundation, the persistent patterns of social and economic inequality provide clarity to the moral injustice of inherited inequalities. Just as the discourse surrounding poverty and "deservingness" has shifted over many years (Gans 1995; Somers and Block 2005; Watkins-Hayes and Kovalsky 2016), I argue that the study of generational inequality offers an analytic and theoretical opportunity for clarifying how many of today's most-pronounced inequalities are disproportionately shaped by the past, as opposed to our individual choices. By studying systematic differences in the temporal dynamics of inequality, my research further emphasizes that today's inequalities are deeply patterned, rather than luck of the draw.

But, first, a note on language. Why do I use the term *generational* inequality over other potential terminology? First, my dissertation is theoretically motivated by a larger intellectual project about understanding the enduring nature of inequalities, over historical time and across generations of families. Second, each chapter invokes different types of generational inequality. Of course, my research involves the study of *intergenerational* inequalities—a term that is used frequently by scholars of social mobility to refer to within-family persistence (or changes) in social status.[1] However, I view the persistence of inequality between parents and children as just one type of generational inequality. My work also touches on within-generational inequalities (over the life course), as well as the population-level persistence of inequalities across generations (or cohorts).

[1] That is, an intergenerational view specifically examines how your parent's status can shape your experiences growing up, and your life experiences can later influence your own children's outcomes.

Ultimately, my dissertation project touches on these three different aspects of generational inequality. In Chapter 2, I investigate *why* the timing of childhood poverty is so influential for children's intergenerational outcomes. In Chapter 3, I explore *how* between-group differences in childhood poverty contribute to intergenerational inequalities, at the individual level, and the generational persistence of racialized inequalities, at the population level. In Chapter 4, I document *how* changes in socioeconomic background have a real, material impact on changes to wealth accumulation and racialized wealth inequality.

1.2 Why Temporal Dynamics?

I argue that temporality is a key element of any social inequality. Every social process is temporally situated and empowered. An inequality has two preconditions: differentiation and effect. First, there must be some form of differentiation. The differentiation can be based on an ascribed status (e.g., below the poverty line, diagnosed with a medical condition) or through an acquired resource (e.g., different levels of income or wealth). At the population level, a person will have a certain probability of experiencing a status or obtaining a resource, where some people have higher likelihoods (or lower likelihoods) of being differentiated into a particular status group or set of resources. Second, there must be some form of effect (or association) of the differentiation, whether it is positive or negative.

Researchers have frequently looked at sources of variation in both of these preconditions—that is, differences in the probabilities of selection into a certain group or status; and differences in the consequences or impact of the initial dif-

ferentiation by status or resource. Many studies examine variation in the effects (or associations) with socioeconomic status. Contextual variation, in particular, has become an emerging source of inspiration for stratification scholarship—examining differences across time and historical contexts (e.g., Bloome, Dyer, and Zhou 2018; Sweeney 2002); geography and spatial contexts (e.g., Curtis and O'Connell 2017; Morenoff 2003); and politics and institutional contexts (e.g., Brady, Finnigan, and Hübgen 2017; Pfeffer and Waitkus 2021).

I argue that temporal exposures offer a fourth source of variation for explaining why certain socioeconomic experiences are more harmful than others. However, unlike the historical, spatial, and political sources of variation, temporal dynamics are a function of the inequality exposure, itself, as opposed to an external, contextual factor.

1.3 Methods for Studying Processes of Inequality

Most of my dissertation uses demographic and quantitative methods to study the dynamics of inequality descriptively, rather than causally. I argue that good descriptive estimates are absolutely *essential* for pursuing certain types of processual questions that cannot be answered by causal estimates.

Under what circumstances is it crucial to adopt demographic and descriptive methods? In my view, demographic methods are well equipped to generate new theories, whereas causal-inference methods are well equipped to rigorously estimate treatment effects. Under strict assumptions, causal estimates can quickly become divorced from the rest of the world, by removing all confounding factors, and isolating the effect of a treatment on a particular outcome. In doing so,

the causal effect loses much of its historical, geographic, and political context. On the other hand, the potential benefits of good descriptive work (like with ethnography or comparative-historical research) are that these methods can be used, flexibly, to examine theoretical processes.

Of course, like all methodologies, descriptive and causal frameworks work best together, in symbiosis, and both approaches require one another for success. However, the questions that I pose in my dissertation often require a flexible analytic strategy for modeling the time and temporal dynamics that characterize the inequality-generating process.

1.4 Three Empirical Demonstrations

This dissertation examines how the temporal dynamics of socioeconomic status contribute to the persistence of generational inequalities over time. Drawing on two empirical cases—family poverty and wealth accumulation—I developed three studies that advance our understanding of how temporal exposures shape long-term processes of social stratification.

In Chapter 2, "The Cumulative Dimension of Timing," I examine *why* temporal exposure (in the timing of childhood poverty) is important for shaping children's later-life outcomes in adulthood. I challenge the dominant explanation for why early-childhood poverty is worse for adult outcomes, compared to later-childhood poverty. I show that systematic differences in the cumulative exposure to poverty offer a better explanation for the stylized fact about early-childhood poverty, compared to the dominant explanation about differences in the magnitude of poverty's age-specific consequences.

In Chapter 3, "The Depth of Temporal Disadvantage," I estimate *how much* of the racialized persistence of economic inequality can be explained by temporal exposures (to the cumulative length of childhood poverty). I show that racial/ethnic inequalities in children's poverty experiences are more extreme than we previously realized—and differences in temporal exposures offer a partial explanation for why Black–White economic inequalities have remained so persistent over time.

In Chapter 4, "The Cumulative Value of Family Origins," I evaluate the monetary *implications* of historical trends in the intergenerational basis for wealth inequality. Although I show that cohort changes in the distribution of socioeconomic background characteristics have had an equalizing effect on Black-White wealth inequality, these changes were entirely offset by other disequalizing factors. And racialized inequalities in parental and childhood characteristics remain the largest contributor to the overall rates of Black-White wealth inequality, regardless of time period or cohort change.

Theoretically, each of my empirical papers is united by a common question about how the temporality of life experiences contributes to social stratification. It is not just *what* happens to you that matters, but *when* something occurs and *how long* it lasts. As a whole, my dissertation advances our understanding of how temporal exposures accumulate into generational inequalities. Ultimately, I argue that systematic differences in year-to-year temporal patterns are fundamental for explaining how certain social inequalities become rigidly stratified.

CHAPTER 2

The Cumulative Dimension of Timing: Early-childhood Poverty and the Persistence of Intergenerational Inequality

2.1 Introduction

In 1964, President Lyndon Johnson launched an expansive legislative agenda, known colloquially as the war on poverty, which sought to reduce intergenerational inequality by improving the material conditions of low-income families with children. Scholars have subsequently shown that poverty rates are strongly correlated with a country's social policies and welfare spending (Brady 2005; Brady 2023; Moller et al. 2003). Since President Johnson's historic

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announcement, there have been decades of research on the devastating effects that poverty and other socioeconomic disadvantages can have on children (see Aber et al. 1997; Heckman and Mosso 2014; McEwen and McEwen 2017). In particular, a broad consensus has emerged, among policymakers and scholars alike, about the importance of early childhood—with many studies finding that young children suffer disproportionately from exposures to poverty (Duncan et al. 1998; Guo 1998), educational disruptions (Currie 2001; Heckman 2006), family instability (Furstenberg and Kiernan 2001; Sik Kim 2011), residential evictions (Leifheit et al. 2020), and even political conflicts (Ramirez and Haas 2021).

In social science research, "timing effects" are sometimes treated as synonymous with "period effects." This can be intuitive, because life-course timing will *always* overlap with a person's age; and historical timing will *always* overlap with the year in which something happens. However, I argue that, in some cases, scholars may be misattributing to *age-specific* effects what are actually a function of *cumulative exposure* effects. Identifying the role of these different dynamics is critical for advancing our understanding of how the timing of social phenomena contributes to the reproduction of inequalities.

I compare these timing dynamics in the context of childhood poverty. The poverty literature presents an ideal setting for studying the effects of timing, because a major finding has emerged, in recent years, showing that early-childhood poverty is associated with lower levels of socioeconomic attainment than later-childhood poverty (Duncan, Ziol-Guest, and Kalil 2010; Lesner 2018; Wagmiller et al. 2006; Ziol-Guest et al. 2012). Scholars have mostly drawn on

developmental theories to understand this phenomenon. The sensitive-age explanation suggests that young children are more vulnerable to the consequences of poverty because disruptions are uniquely harmful during the earliest stages of child development and maturation (Duncan, Magnuson, and Votruba-Drzal 2017:422–425). Early-childhood poverty—typically defined as poverty that occurs before age five or six—is most detrimental for young children because it impedes a critical period of cognitive skill acquisition, social-emotional advancement (Cunha and Heckman 2007; Kulic et al. 2019), and neurobiological brain development (Fox, Levitt, and Nelson 2010; McEwen and McEwen 2017).

However, I propose that theories of cumulative (dis)advantage can provide a competing perspective for understanding why early-childhood poverty has an outsize influence on socioeconomic attainment (see DiPrete and Eirich 2006:280–281). We know that poverty is harmful for people at all ages—with the negative effects of poverty affecting children, working-age adults, and older-age adults (Lichter 1997; Willson, Shuey, and Elder 2007). We also know that longer exposures to poverty are worse than shorter exposures to poverty (Alvarado 2016; Aue, Roosen, and Jensen 2016; Guo 1998). Therefore, an alternate explanation for the outsize consequences of early-childhood poverty is that, when children experience poverty at a young age, they spend a longer length of time in poverty, across the entirety of childhood.

In testing the cumulative-exposure explanation, and putting it into conversation with the sensitive-age explanation, I draw on a rich sociological literature of life-course trajectories (e.g., Cheng and Song 2019; Elder 1985) and cumulative advantage processes (e.g., Allison, Long, and Krauze 1982; Cheng 2016). It is

critical to evaluate these two explanations because they each signify a different set of mechanisms through which poverty exacts a toll on children, and these theories can have significant implications for scholars and policymakers who are committed to reducing poverty.

Which theoretical perspective best explains why early-childhood poverty is associated with worse socioeconomic outcomes than later-childhood poverty: the sensitive-age explanation or the cumulative-exposure explanation? To address this question, I examine how much variation in adult income is explained by the different dynamics of children's poverty timing. However, there are two empirical problems that must be attended to. First, if age-specific exposures are correlated with the total exposure to poverty, then the overlapping nature of these two dynamics presents a multicollinearity problem that must be carefully modeled. To deal with this empirical challenge, I develop a flexible empirical approach for measuring the consequences of dynamic characteristics—namely, by isolating the influence of one dynamic and restricting the comparison to people with identical values on the other dynamic. Second, social scientists have traditionally modeled the consequences of poverty in ways that cannot differentiate the role of different dynamics (e.g., Lee 2014; Wagmiller et al. 2006) or in ways that make it difficult to estimate poverty's cumulative effects, by controlling for variation in every other childhood interval (e.g., Duncan et al. 2010; Lesner 2018). Failure to address these two empirical problems could mean that previous research has misattributed the theoretical explanation for why the timing of childhood poverty shapes adult socioeconomic outcomes.

Drawing on 52 years of data from the Panel Study of Income Dynamics, I show that exposures to poverty at a young age are highly correlated with the total amount of time that a child spends in poverty, across the entirety of childhood. Next, I estimate how much variation in adult income is explained by the different dynamics of childhood poverty. Through careful measurement and modeling, I find that a child's total exposure to poverty explains the vast majority of variation in adult income, compared to differences in the magnitude of poverty's age-specific consequences. An extra year of childhood poverty is associated with an average loss of 1,600 dollars in annual income when children reach their thirties. Finally, I use a mediation approach to estimate how much of the total association between early-childhood poverty and adult income may operate through variation in children's later-childhood poverty experiences. I find that roughly half of the early-childhood association is explained by children's subsequent exposures to poverty, during the remainder of childhood.

This study makes three key contributions to sociology, with broad significance for scholars across the social sciences. First, in the context of poverty, these findings challenge the prevailing explanation for why early-childhood poverty generates worse socioeconomic outcomes than later-childhood poverty. I find no evidence that young children suffer larger consequences from poverty, because it is uniquely harmful during the earliest stages of development. Second, this study provides an empirical demonstration of what I refer to as the cumulative dimension of timing—when timing differences can be explained by correlations with the total amount of exposure to an event, status, or related quantity—as opposed to the chronological dimension of timing, which fore-

grounds the specific period in which something happens. These insights extend well beyond the context of poverty. Any researcher who studies the timing of a social phenomenon should investigate the role of cumulative exposures before drawing conclusions about period-specific factors that might explain variation in exposure timing. Third, I developed a flexible empirical approach for disentangling the consequences of different dynamic characteristics. I use this approach to study the timing of childhood poverty, but scholars can apply this empirical strategy to study the temporal patterns of health events, employment spells, family transitions, and any other dynamic processes. I conclude by discussing how this study's findings are relevant to scholars and policymakers who are engaged in poverty-reduction efforts.

2.2 The Timing of Childhood Poverty

There is strong evidence that demonstrates how children who experience poverty have worse outcomes in adulthood, compared to children who never experience poverty (Lichter 1997). And a subset of this research has examined differences in the timing of exposure to poverty, showing that long-run associations with poverty are larger in certain periods of childhood (see Duncan et al. 2017). In this section, I review studies that engage, theoretically and empirically, with the relationship between the timing of childhood poverty and children's adult outcomes. Most studies are consistent in identifying early childhood as having the largest consequences for children's level of socioeconomic attainment, though there is more variation in research on other types of outcomes.

2.2.1 Associations with Socioeconomic Attainment

Many studies have found that early-childhood poverty experiences are associated with larger socioeconomic consequences than later-childhood poverty experiences (Duncan et al. 2010; Duncan et al. 1998; Guo 1998; Liu and Hannum 2017; Ristikari, Merikukka, and Hakovirta 2018; Wagmiller et al. 2006; Ziol-Guest et al. 2012), though there are a few notable exceptions (Bask et al. 2021; Lee 2014; Lesner 2018). Socioeconomic outcomes—such as income, wages, education, and occupational characteristics—show that a person's family background shapes their level of socioeconomic attainment in adulthood.

In the 1990s, scholars began to compare how the influence of poverty varies across different periods of childhood. Duncan and colleagues (1998) first examined the influence of early-childhood, middle-childhood, and adolescent exposures to poverty-level incomes on two measures of education. The authors found that children from families with poverty-level income had the lowest levels of each educational outcome (years of completed schooling and the probability of high school completion). In the same year, Guo (1998) further differentiated between the types of educational outcomes, by studying academic achievement and cognitive ability. He found that early-childhood exposures to poverty were more highly associated with 'ability' outcomes than adolescent exposures; and 'achievement' outcomes were more highly associated with later-childhood poverty exposures. The results of these studies suggested that there may be variation across outcomes—and that findings may also be sensitive to measurement and analytic decisions about how scholars study their key variables of interest.

Duncan and colleagues have replicated their findings several times with an expanded list of socioeconomic outcomes. Using the same approach as the original 1998 study, these authors found that early-childhood exposures to poverty-level incomes were associated with worse socioeconomic outcomes—reduced annual wages, a smaller number of annual hours worked, an increased rate of welfare receipt, and fewer years of schooling—compared to exposures in later childhood (Duncan et al. 2010; Kalil, Duncan, and Ziol-Guest 2016; Ziol-Guest, Duncan, and Kalil 2009; Ziol-Guest et al. 2012). Other scholars have corroborated these results, using latent-class analyses to compare children's poverty trajectories, from which they drew the same conclusions about the outsize influence of early-childhood poverty on children's socioeconomic outcomes (Wagmiller et al. 2006).

Although there is a growing consensus about how early-childhood poverty is more highly associated with socioeconomic attainment than later-childhood poverty, there are a few exceptions. Some studies have identified no clear or discernible differences in the timing of exposure (Lee 2014), whereas other studies have identified discordant results about whether early-childhood exposures have the largest socioeconomic consequences (Bask et al. 2021; Lesner 2018). But, generally speaking, most studies have found that early-childhood poverty exposures may have an outsize influence on adult income, educational milestones, and other measures of socioeconomic attainment.

2.2.2 Variation in the Associations with Other Adult Outcomes

Unlike with socioeconomic attainment, there is mixed evidence about how the timing of childhood poverty shapes children's health and behavioral outcomes in adulthood (e.g., Bask et al. 2021; Duncan et al. 2010; Lesner 2018; Najman et al. 2010; Ristikari et al. 2018). For health outcomes, there is mixed evidence about the influence of poverty timing, with some studies finding that children had worse physical health if they were exposed to early-childhood poverty (Li, Mustillo, and Anderson 2018; Vartanian and Houser 2012; Ziol-Guest et al. 2009), whereas other studies found no timing differences (Duncan et al. 2010) or larger health consequences of poverty exposures in later childhood (Brady et al. 2022; Shuey and Willson 2014). Finally, for certain behavioral outcomes, most studies identified adolescent poverty as the most consequential interval for children's behavioral outcomes in adulthood—which include substance use and drug-related disorders (Najman et al. 2010); the probability of a criminal conviction (Bask et al. 2021); and experiences of early-life or nonmarital fertility (Duncan et al. 2010).

Every study found that exposures to childhood poverty—at any age of childhood—was harmful for children (e.g., Lichter 1997; Willson et al. 2007). Where studies differ is regarding the role that the timing of exposure plays in shaping adult outcomes. Although there was mixed evidence for children's health and behavioral outcomes in adulthood, a majority of studies found that exposures to early-childhood poverty were associated with lower levels of socioeconomic attainment than later-childhood poverty (see Duncan et al. 2017:422-425).

2.2.3 Correlations in the Dynamic Experiences of Childhood Poverty

Some studies of poverty timing have also identified a strong link between children's total exposure to poverty and their long-run outcomes (e.g., Guo 1998; Lesner 2018; Najman et al. 2009). Yet, the developmental perspective has served as the primary framework for interpreting timing effects, emphasizing differences in period-specific exposures, rather than differences in cumulative exposure. However, the dynamics of poverty are highly correlated with one another. And such a correlation could introduce a competing explanation for why early-childhood poverty is associated with worse socioeconomic attainment than later-childhood poverty.

There are two key descriptive patterns that characterize how poverty varies across childhood. First, younger children are more likely to experience poverty than their older peers (Rank and Hirschl 1999). This is largely due to the fact that children's parents are aging at the same time that children move through childhood; and adult incomes tend to increase across their own life course (e.g., Bloome and Furey 2020). (By definition, older children have older parents, relative to when they were younger.) Second, poverty exposures tend to be brief—better characterized as "episodic" than "chronic" (Devine, Plunkett, and Wright 1992). Many families will enter poverty for a short period of time due to an economic shock, such as a brief period of unemployment or a change in family structure (Bane and Ellwood 1986; Stevens 1994), and the family will exit poverty after recovering from the initial shock. But there is considerable variation in these two empirical facts.

At any given age, between 12 and 16 percent of American children were experiencing poverty—based on a sample of people born between 1967 and 1982. (These patterns are highlighted in Figure 2.1.) Using longitudinal survey data, it becomes clear that four-out-of-ten American children were exposed to poverty by the time that they celebrated their sixteenth birthdays (42 percent of the entire cohort). Although a brief exposure was the most common poverty experience, Figure 2.1 shows that the amount of children who experienced a single year in poverty is equal to the amount of children who experienced poverty for more than half of childhood (i.e., eight or more years in poverty).

Notably, among American children who experienced poverty, nearly three-quarters had their first exposure to poverty before their sixth birthdays (31 percent of the entire cohort). This is an extremely informative statistic because it means that three times as many children experienced their first exposure to poverty between birth and age 5, as opposed to the ages of 6 and 15. Yet, the year-to-year rates of childhood poverty never fell below 12 percent. Therefore, the majority of children who experience poverty after the age of six are experiencing a recurrent exposure to poverty (rather than a first exposure).

These patterns highlight the overlapping nature of dynamic characteristics. Most children who experience poverty at older ages were first exposed to poverty at a young age. When children experience poverty at a young age, they have a higher likelihood of experiencing persistent poverty, compared to their peers who never experienced poverty in early childhood. As a result, there may be a strong correlation between a child's period of exposure to poverty and the total length of time that they spend in poverty. This correlation between

the dynamics of poverty must be addressed, in order to identify why exposure timing is associated with children's long-run outcomes.

2.2.4 Explaining the Outsize Consequences of Early-childhood Poverty

The core objective of this study is to understand why early-childhood poverty might be associated with worse socioeconomic outcomes than later-childhood poverty. I compare two theories that might explain these outsize consequences: (1) the sensitive-age explanation, which has emerged as the dominant explanation in the poverty literature; and (2) the cumulative-exposure explanation, which I propose as an alternate perspective to explain why the timing of childhood poverty exposures might shape children's socioeconomic attainment. Below, I outline three of the theoretical interventions that this study makes to the literature, followed by a more detailed overview of the empirical strategy that I use to evaluate these questions.

First, I begin by establishing the correlation between children's age-specific exposures and their amount of total exposure to poverty. I present evidence showing that children who are exposed to early-childhood poverty tend to experience poverty for a longer duration of childhood, relative to their peers who are do not experience poverty at a young age.

Because of this correlation, I argue that the cumulative dimension of timing may offer a competing explanation for why early-childhood poverty is associated with worse socioeconomic outcomes than later-childhood poverty. There has not been meaningfully considered as an alternate explanation in the literature, which means that even the dominant perspective—the sensitive-age

explanation—has not been tested empirically. Instead, studies interpret timing differences as *prima facie* evidence of theoretical explanations that emphasize the unique features of the period of exposure. This study addresses this omission by proposing a competing perspective—the cumulative-exposure explanation—and evaluating the evidence for each of these theoretical perspectives.

Second, I examine whether the age-specific consequences of poverty are more severe for young children than they are for older children—after controlling for any systematic differences in poverty duration. Using my empirical approach for disentangling dynamic characteristics, I show that the age-specific consequences of poverty do not explain variation in children's socioeconomic attainment. Among children who experience the same number of years in poverty, across the entirety of childhood, there is a negligible relationship between children's adult income attainment and the age at which they were exposed to poverty.

In light of these findings, there is not sufficient evidence to support the sensitive-age explanation. Previous studies have provided robust evidence that children's timing of poverty exposures is associated with their adult outcomes, but I argue that their conclusions about age-specific effects and developmental mechanisms that explain these differences by exposure timing may have been premature. Instead, the variation that is explained by children's duration of exposure to poverty warrants further investigation into alternate explanations. This study advances the literature by evaluating the cumulative-exposure explanation as a competing theory for why the timing of childhood poverty matters.

Third, I use a mediation approach to examine how much of the association between adult income and early-childhood poverty attenuates after conditioning on children's subsequent exposures to poverty during the remainder of childhood. I estimate that roughly half of the early-childhood poverty association may operate through children's experiences with poverty in later childhood.

Based on these findings, I argue that the outsize associations with early-childhood poverty are better explained by children's cumulative exposure to poverty, rather than differences in the magnitude of age-specific consequences.

2.3 Empirical Strategy

In this section, I describe how I measured the conditional and unconditional associations between adult income and the timing of childhood poverty. Next, I outline the analytic approach that I used to disentangle the consequences of dynamic characteristics that are correlated with one another. Finally, I explain the mediation approach that I used to estimate the cumulative effects of poverty.

2.3.1 Describing the Dynamics of Childhood Poverty: Total Associations with Adult Income

To evaluate the stylized fact regarding the outsize associations with early-childhood poverty, I compare the total associations between adult income and the number of years that a child spends in early-childhood and later-childhood poverty, respectively. Throughout this study, I measure early- and later-childhood poverty at ages 0 to 5 and 6 to 15, respectively, and I assess adult income when children are between the ages of 30 and 39.

I initially estimate total associations—rather than partial associations that might control for poverty (or other socioeconomic characteristics) that occur in subsequent periods of childhood—because these covariates offer a possible pathway through which poverty influences children's adult outcomes.[1,2] If the age-specific consequences of poverty are more harmful for younger children than for older children, then we might expect to observe a larger total association with early-childhood poverty, through all possible pathways, compared to the total association with later-childhood poverty.

2.3.2 A Flexible Empirical Approach for Disentangling Dynamic Characteristics

The primary goal of this study is to differentiate the consequences of age-specific exposures to poverty—characteristic of the sensitive-age explanation—and the consequences of the total exposure to poverty—characteristic of the cumulative-exposure explanation. However, the dynamics of poverty are highly correlated (see Figure 2.1). To deal with this multicollinearity problem, I develop and implement an empirical approach for disentangling the influence of dynamic characteristics.

First, I construct measures that directly correspond to each dynamic characteristic as closely as possible. For the total exposure to poverty, I use a count

[1] I use the term "total association" to mean the zero-order correlation coefficient, between two variables, without the inclusion of any other covariates.

[2] For example, if I immediately estimate the influence of early-childhood poverty, net of later-childhood poverty, then I would be starting with an approach that precludes the cumulative-exposure explanation—whereby the outsize associations with early-childhood poverty are partially mediated by the increased probabilities of experiencing later-childhood poverty.

of the number of years that a child spends in poverty across the entirety of childhood (ranging from 0 to 16). For the age-specific exposure to early-childhood poverty, I calculate the proportion of early childhood that children spend in poverty (ranging from 0.0 to 1.0).[3]

Second, I examine the amount of variance explained by a single dynamic characteristic, by restricting comparisons to children who have identical values on all other dynamics. This is the essential feature of the approach for disentangling the consequences of dynamic characteristics. For the current study, I want to assess whether the outsize associations with early-childhood poverty are due to differences in the *age-specific exposures* to poverty. This mean that the magnitude of consequences are larger for an age-specific exposure to early-childhood poverty than for an equal exposure to later-childhood poverty, which would be consistent with the sensitive-age explanation.

For example, we can imagine two children who both experience four years of poverty, across the entire period of childhood. But one child experiences all four years of poverty during early childhood, and the other child does not experience any poverty during early childhood (e.g., they experience four years of poverty during adolescence). If the sensitive-age explanation is correct, then we would expect to observe worse outcomes for the child who was exposed to four years of poverty in early childhood, compared to their peer who experienced the same total exposure but with zero years of poverty occurring in early childhood.

[3]Given how I define early childhood (ages 0 to 5), a child is eligible to experience up to six years in early-childhood poverty. Therefore, children who experiences zero years, three years, and all six years of their early childhoods in poverty will be assigned values of 0.0, 0.5, and 1.0, respectively.

Equation (2.1) formalizes the empirical approach that I outlined above. Using a linear regression, I generate estimates of the association between the outcome and the first dynamic of interest, $\boldsymbol{D1_i}$, while holding constant the second dynamic, $\boldsymbol{D2_i}$, and adjusting for a matrix of covariates, $\boldsymbol{C_i}$.[4] What is essential, here, is that the influence of $\boldsymbol{D1_i}$ is completely isolated by restricting all comparisons to children with identical values of $\boldsymbol{D2_i}$.

$$\boldsymbol{Y}_i \;=\; \boldsymbol{D1}_i \;+\; \sum_{n=1}^{N} \Big[\boldsymbol{D2}_i = n\Big] \;+\; \boldsymbol{C}_i \;+\; \epsilon_i \tag{2.1}$$

In Equation (2.2), I take this approach for disentangling dynamic characteristics and I apply it to the dynamics of childhood poverty. I do so by estimating the association between adult income, $\boldsymbol{Income}_i$, and the age-specific exposure to poverty, $\boldsymbol{PrEarly}_i$, measured by the proportion of early childhood that each child i spends in poverty—net of controls variables for each value of total exposure to poverty, $\boldsymbol{TotalEx}_i$. I use a series of 16 dummy variables (sometimes referred to as fixed-effect controls) to ensure that children are compared only to their peers with an identical amount of total exposure to poverty.[5,6]

[4] Every model includes a vector of covariates that include: child gender, race, and birth year; region of residence; and number of siblings. Additionally, standard errors are clustered to account for sampling strata and family-level membership.

[5] There is a dummy variable for all but one of the possible values of total exposure to poverty; zero years of total exposure to poverty is omitted from the model, as the reference category.

[6] I do not use continuous covariates to control for the competing dynamics, because there may be some variation around the covariate's conditional mean. By comparison, dummy variables ensure that children are only being compared to other children who have identical values of the control variable.

$$\boldsymbol{Income}_i \;=\; \lambda_0 \;+\; \lambda_1 \cdot \boldsymbol{PrEarly}_i \;+\; \sum_{n=1}^{N} \Big[\lambda_n \cdot \boldsymbol{TotalEx}_i = n\Big] \;+\; \boldsymbol{C_i} \;+\; \epsilon_i \tag{2.2}$$

For these models, the key coefficient is the lambda, λ_1, which represents the unique influence of children's exposure to early-childhood poverty, net of their total exposure across childhood. A larger effect size of the key association (i.e., a steeper curve, when displayed graphically) means that the main dynamic characteristic explains a greater amount of variance in the outcome. A null effect (i.e., a relatively flat curve) indicates that the main dynamic characteristic being modeled explains a smaller amount of variance in the outcome, among children who have the same value on the corresponding dynamic characteristics.

2.3.3 Estimating the Influence of Cumulative Exposures: A Mediation Approach

Finally, I estimate how much of the association with early-childhood poverty might be explained by children's cumulative experiences of poverty, during the remainder of childhood. As a first step, I produce two linear regressions of adult income on children's exposure to early-childhood poverty, with and without controls for subsequent exposures to poverty. These two regressions are outlined in Equations (2.3) and (2.4).

In each equation, I regress adult income, $\boldsymbol{Income_i}$, on the number of years spent in early-childhood poverty, $\boldsymbol{EarlyEx_i}$, as well as several demographic control variables, represented by $\boldsymbol{C}_i$. The only difference between the two re-

gression equations is that Equation (2.4) introduces a series of dummy variables, ranging from 1 to K, in order to compare children with the exact same number of years in later-childhood poverty ($\boldsymbol{LaterEx_i}$). I refer to the first regression as the *unconditional* association with early-childhood poverty, and the second regression represents the *conditional* association with early-childhood poverty, net of the length of time that a child spent in later-childhood poverty.

$$\boldsymbol{Income}_i \;=\; \alpha_0 \;+\; \alpha_1 \cdot \boldsymbol{EarlyEx}_i \;+\; \boldsymbol{C_i} \;+\; \epsilon_i \tag{2.3}$$

$$\boldsymbol{Income}_i \;=\; \beta_0 \;+\; \beta_1 \cdot \boldsymbol{EarlyEx}_i \;+\; \sum_{k=1}^{K} \Big[\beta_k \cdot \boldsymbol{LaterEx}_i\Big] \;+\; \boldsymbol{C_i} \;+\; \epsilon_i \tag{2.4}$$

As a second step, I estimate how much of the unconditional association with early-childhood poverty is mediated by later-childhood poverty. The mediation approach that I use is described in detail by Imai, Keele, and Yamamoto (2010). I use Stata to generate the estimates of the mediation analysis, implemented by Hicks and Tingley (2011).

A simplified representation of the mediation approach is outlined in Equation (2.5). Effectively, the mediated component can be estimated by taking the unconditional association with early-childhood poverty—denoted by α_1, from Equation (2.3)—and subtracting it by the conditional association that controls for children's later-childhood poverty—denoted by β_1, from Equation (2.4).[7]

[7]The conditional and mediated components are sometimes referred to as the direct and indirect effects, which, when summed together, represent the total effect.

$$\underbrace{\delta\left(\boldsymbol{EarlyEx}\right)}_{\substack{\text{Mediated}\\\text{difference}}} = \underbrace{\alpha_1}_{\substack{\text{Unconditional}\\\text{association}}} - \underbrace{\beta_1}_{\substack{\text{Conditional}\\\text{association}}} \tag{2.5}$$

Together, the difference between coefficients (δ) represents the amount of the unconditional association with early-childhood poverty that operates through children's subsequent poverty experiences during the rest of childhood.

2.4 Data and Sample

The ideal data for estimating the influence of children's poverty timing on adult socioeconomic attainment require both (*i*) repeated measures of income and (*ii*) families being observed for at least two generations. I use the Panel Study of Income Dynamics (PSID), because of its unique features as the world's longest-running longitudinal household survey, which began in 1968 with a nationally representative panel of more than 5,000 families in the United States. Crucially, the survey has continued to interview each family and their children, even after a child moves out from the parental home to form their own independent household. The specific data file that I used to construct my sample comes from the PSID's Social, Health, and Economic Longitudinal File (PSID-SHELF), due to its harmonized socioeconomic measures and multigenerational data structure (Daumler, Friedman, and Pfeffer 2025).

I have three inclusion criteria for my analytic sample. (1) My main population of interest comprises children who were born between the years of

1967 and 1982, which amounts to an initial group of 6,721 respondents.[8] (2) Because the central focus of this study is to disentangle the dynamics of childhood poverty, I require that children be observed annually for their entire childhoods—every year, between the ages of 0 and 15. This restriction reduces my sample to 3,501 respondents, due to year-to-year nonresponse. Finally, (3) I measure children's adult outcomes during their thirties—between the ages of 30 and 39—and I require income observations for at least two out of the five waves (following the PSID's switch to biennial interviews). This culminates in a final analytic sample of 1,909 respondents, for whom I can observe their entire childhoods and assess their eventual outcomes as adults. Additionally, due to the PSID's oversample of low-income families, half of my analytic sample (936 respondents) were exposed to at least one year of poverty in childhood, which is important for my analyses of variation in the dynamics of poverty.

Due to the data-intensive requirements for inclusion in my sample, I create my own set of analytic weights that are a function of (*i*) the original 1968 family weights, (*ii*) multiplied by the inverse probability of being included in my sample.[9] Adjusted analyses assign greater weight to individuals who have characteristics that are least likely to be included in my analytic sample. By contrast, unadjusted analyses would underestimate the rates of poverty, if individuals who experience poverty are more likely to attrit from the PSID *or* if these same

[8]I restrict the sample to children born in 1967 or later to ensure that I do not miss any observations of child income after a child is born (given that the 1968 survey wave asks families about their income in the preceding year). Additionally, I only include children who were born in 1982 or earlier, because the youngest birth cohort will experience their 15th birthdays in 1997, when the PSID switches from annual to biennial data collection.

[9]I follow the weighting procedure that is recommended by Heeringa, West, and Berglund (2017:42–46).

individuals are least likely to satisfy the inclusion criteria for my sample.[10] As a result, my weighted estimates should be nationally representative of American households in 1968 and all newly born descendants to these families.

Next, I construct a comprehensive set of measures for income and poverty status. For this study, I calculate each person's mean value of income when they are in their thirties. I use an equivalized measure of disposable family income, expressed in 2018 dollars, averaging across all available observations between the ages of 30 and 39.[11] Following the recommendation of Brady et al. (2018), I use a relative measure of poverty, by calculating a poverty threshold that is 50 percent of the median income in each year (using the same equivalized measure of disposable family income). When a child's family income falls below this threshold, they are coded as having experienced poverty during that particular year. As a robustness check, I rerun all analyses using five different measures of poverty, but I find that my results are consistent across these alternative specifications.[12]

[10] Although the PSID provides researchers with survey weights that adjust for the first source of potential bias (i.e., survey attrition), the PSID-provided weights would not adjust for respondents who continue to be active participants in the PSID but are excluded from my sample for analytic reasons (e.g., for simply missing one survey year during childhood).

[11] First, I calculate each family's post-tax and post-transfer income (as opposed to individual earnings, individual income, or pre-tax family income). Second, I equivalize income for family size (by dividing income by the square root of the number of people in the family unit). Finally, I adjust for inflation, using the Personal Consumption Expenditures Price Index, and income values are expressed in 2018 dollars.

[12] In total, I calculate four relative measures of poverty—with and without adjustments to post-tax and post-transfer income; and with and without adjustments for family size—and I calculate two absolute measures of poverty—using the Census's official poverty threshold that they report discretely for families of different sizes. (In unreported analyses, I complete robustness checks with each of the alternate measures of income and poverty status. The manuscript's findings were not sensitive to the use of these alternate measures. Please note that the results of these analyses are available upon request.)

To measure the consequences of poverty timing, I compare children's poverty experiences in early childhood—which I define as ages 0 to 5—and later childhood—which I define as ages 6 to 15.[13] I assess children's outcomes during their thirties—using all available observations between the ages of 30 and 39. I select adult income as the main outcome for the study, rather than the probability of experiencing adult poverty, because averaging across a continuous measure of income offers a better approximation of adult socioeconomic attainment than averaging across a discrete count of poverty for a subset of years. When there are only a small number of observations available, there will be a strong underestimate of the rates of adult poverty,[14] whereas Brady et al. (2018:336) show that averaging across 2 to 5 years of income observations explains most of the variation in permanent income. Therefore, I chose to display results for analyses of mean adult income, because I consider it to be a better measure when there are fewer observations during the interval being studied.

Finally, I create several pretreatment measures of children's demographic characteristics, including: (1) gender (a binary indicator, in which male children are in the reference group); (2) race (a binary indicator, in which children who are not racialized as Black are in the reference group); (3) birth year (a contin-

[13] Methodologically, this definition of early childhood is consistent with previous studies of childhood poverty (e.g., Duncan et al. 1998:412), and, theoretically, studies of child development have long argued that the first six years of life constitute a unique and crucial stage of cognitive and noncognitive development (see Duncan et al. 2017; Kulic et al. 2019).

[14] Because longer periods of observation (e.g., a 16-year interval, commensurate with how I examine childhood) will always yield a higher prevalence of poverty than a shorter period of observation (e.g., a 5-year interval), particularly because a large number of families experience poverty for only a single year (see Figure 2.1).

uous variable that is mean-centered at 1975); (4) region of residence (a binary indicator, in which children who live outside the South are in the reference group); and (5) number of siblings (a continuous variable that is mean-centered at two children). I also collect the PSID's variables for sampling strata and an indicator of family-level membership, in order to cluster my standard errors.

2.5 The Correlated Dynamics of Childhood Poverty

Childhood poverty generates inequalities that are far-reaching and extend into adulthood. In this section, I examine how children's adult incomes are shaped by their timing of exposure to poverty—a topic that has received considerable attention (see Duncan et al. 2017). Finally, I present two possible explanations for this empirical finding, and I conclude by showing that the poverty dynamics that underlie these two explanations are strongly correlated with one another.

Children who grow up in poverty have lower incomes, as adults, compared to their peers who did not grow up in poverty. Figure 2.2 highlights the difference in mean adult income by childhood poverty status. People who experienced at least one year of poverty as children have incomes that are 15,000 dollars lower, on average, than people who did not experience poverty as children (34,600 versus 50,400 dollars).

Children who were exposed to poverty also have a higher probability of remaining at the bottom of the income distribution, relative to their peers who were never exposed to poverty. In addition to the difference in means, Figure 2.2 shows that childhood poverty also affects a person's relative position in the income distribution. The median income for people who experienced child-

hood poverty (29,000 dollars) is substantially lower than the median income for people who did not experience poverty (43,400 dollars), and, notably, it is even below than the 25th-percentile income of their more-advantaged peers (30,900 dollars).

One key source of variation is children's timing of exposure to poverty. For many socioeconomic outcomes, scholars have found that the consequences of early-childhood poverty are worse than the consequences of later-childhood poverty (Duncan et al. 2017). Figure 2.3 provides evidence that is consistent with the stylized fact that can be found in the literature. I show that an exposure to poverty between the ages of 0 and 5 is associated with a larger decrease in adult income than an equal exposure to poverty that occurs between the ages of 6 and 15. In fact, for each additional year of early-childhood poverty, a person's income is reduced by 4900 dollars, as compared to a 3400 dollar decrease that is associated with an additional year of later-childhood poverty.

While these results provide suggestive evidence about the outsize associations with early-childhood poverty, they do not provide definitive evidence about what explains the relative size of the two associations. Some people might conclude, for example, that the heterogeneous consequences of poverty timing are due to differences in magnitude of effects that children experience at specific ages—represented, in panel (a) of Figure 2.4.

However, I propose that timing effects may also have a cumulative dimension. To illustrate the logic of this alternate explanation, I examine the association of adult income with the total number of years that a child spends in poverty across the entirety of childhood—highlighted in panel (b) of Figure

2.4. Children who are exposed to poverty for a longer duration of childhood tend to have lower incomes, compared to their peers who experienced poverty for shorter lengths of time.

But how can timing effects be explained without differences in age-specific exposures? If there is overlap between the two dimensions of poverty timing, then the heterogeneous consequences might be a function of children's duration of exposure to poverty, rather than their age-specific exposures.

In fact, there is a strong correlation between the age-specific and cumulative exposures to poverty. I present evidence of this correlation in panel (c) of Figure 2.4—represented by the mean number of years that a child spends in poverty across childhood, according to the age at which they are first exposed to poverty. Children who are born into families in poverty can expect to spend more than half of their childhoods in poverty (8.1 years, on average, for children who are first exposed to poverty at age zero). Strikingly, children who are exposed to poverty just two years later can expect to spend half as much time in poverty, compared to children who are born into families in poverty (4.3 years, for children who are first exposed to poverty at age two). Even a small difference in a child's age of first exposure (e.g., two years older at first exposure) is associated with large differences in the length of time that a child spends in poverty during the remainder of childhood (i.e., four extra years spent in poverty).[15]

It is essential to account for the correlation between these dimensions of poverty timing, in order to adjudicate between the two explanations for why

[15] This reduction is larger than what one would expect (1) if poverty was randomly distributed or (2) if the total exposure to poverty was solely a function of the remaining number of years spent in poverty after the initial exposure.

early-childhood poverty is associated with worse socioeconomic outcomes than later-childhood poverty. To accomplish this, I develop and implement an empirical approach for disentangling the consequences of different dynamic characteristics.

2.6 The Marginal Influence of Age-specific Exposures, Net of Duration

The central goal of this study is to examine how much variance in children's adult income is explained by the age-specific consequences of early-childhood poverty, after controlling for differences in total exposure. Using my empirical approach to disentangle the influence of dynamic characteristics, I show that there are no additional consequences from being exposed to poverty at younger ages, as opposed to older ages, net of poverty duration. Therefore, the outsize influence of early-childhood poverty may be better explained by differences in children's total exposure to poverty, rather than differences in the magnitude of consequences from experiencing poverty at a young age.

As one might expect, people who spend more time in poverty, as children, have lower levels of socioeconomic attainment than people who spent a smaller share of childhood in poverty. In panel (a) of Figure 2.5, there is a steep negative association between income, on the Y-axis, and children's total exposure to poverty, on the X-axis. On average, an additional year of poverty is associated with a 1600-dollar loss in children's adult-aged income. Given the strength of this association, it becomes especially important to account for the competing

influence of total exposure when examining (and making claims about) the age-specific consequences of poverty.

Next, I estimate the association between adult income and children's age-specific exposures to poverty at younger ages, net of how many years that they spent in poverty across the entirety of childhood. By restricting comparisons to children who were exposed to poverty for the same number of years, I ensure that children's age-specific exposures are uncorrelated with the duration of exposure to poverty. For example, if a number of children are each exposed to poverty for a total of five years, we would expect to observe larger consequences for children who experience *all five years* in early-childhood poverty (i.e., before age 6), relative to children who experienced *all five years* in later-childhood poverty (i.e., age 6 or later). However, I do not find this to be the case.

In the second row of Figure 2.5, I show that adult incomes, plotted on the Y-axis, are weakly associated with children's age-specific exposures to poverty, plotted on the X-axis. Whereas steeper slopes indicate that a predictor has a larger association with an outcome, the flat slopes that are displayed in panel (b) suggests that there is a marginal or negligible association with adult income. This means that, among children who experience poverty for an equal length of time, there are no additional consequences from being exposed to early-childhood poverty, as opposed to later-childhood poverty. Statistically, this relationship is estimated imprecisely, exemplified by the large standard errors presented in panel (c) of Figure 2.5; but, substantively, the point estimate indicates a null association, as evidenced by the flat curve in panel (b) and the inability to distinguish the marginal association from zero in panel (c).

As a final robustness check, I examine whether there is any heterogeneity in the influence of age-specific exposures. In statistical terms, I add an interaction between the two dynamic characteristics. Therefore, I allow for different slopes for multiple groups of children, who share the same duration of exposure to poverty. We can think of this as the most conservative approach for establishing that age-specific exposures do not influence adult income after adjusting for variation in children's total exposures to poverty across childhood.

Overall, the consequences of experiencing poverty at a young age continue to be modest, even after adding interaction term between age-specific exposures and children's duration of exposure to poverty. Figure 2.6 presents 16 discrete plots that display the influence of age-specific exposures at each level of poverty duration. Due to the small number of respondents in each subgroup, standard errors are not displayed.[16] The goal is not to provide precise estimates for a detailed subgroup analysis. Instead, these results are intended to supplement the main analyses that were presented in Figure 2.5, by identifying potential heterogeneity in the relationship between adult income and age-specific exposures to poverty.

Although there is some variation across the groups in Figure 2.6, these fluctuations do not appear to increase or decrease in a systematic pattern. Therefore, it is safe to interpret the relationship that is estimated on the entire sample, highlighted in panel (a), for all children. Even with a more conservative modeling

[16]Children who experienced 10 years of poverty represent the smallest subgroup—and the only subgroup to have fewer than 30 respondents ($N_{ypov=10}$ = 28). Excluding respondents from the three largest subgroups, with over 100 respondents apiece, the average subgroup has more than 40 respondents ($\overline{N}_{ypov=3-16}$ = 44.)

approach, I continue to find that children's age-specific exposures are weakly associated with adult income.

Taken together, these results suggest that the consequences of age-specific exposures do not explain children's socioeconomic attainment—and almost all of the variance in adult-aged income is explained by variation in children's duration of total exposure to poverty. Further investigation is warranted—to explore how the effects of poverty timing might operate through cumulative advantage processes.

2.7 Poverty Timing and the Significance of Cumulative Exposures

In this section, I explore how well the theory of cumulative disadvantage explains why early-childhood poverty is associated with worse socioeconomic attainment than later-childhood poverty. By documenting the cumulative probabilities of poverty, I show that children's early-childhood poverty experiences are a strong predictor of their later-childhood poverty experiences. But how much of this persistence is a cumulative effect of the initial poverty exposure? To answer this question, I use a mediation analysis to examine how much of the association with early-childhood poverty operates through subsequent exposures to poverty.

Children's poverty histories are a major determinant of their future exposures. In Table 2.1, I describe the cumulative probabilities of experiencing poverty, conditional on early-childhood exposures. It is possible for children to experience between zero and six years of poverty in early childhood (ranging from birth to age 5). For each measure of later-childhood poverty, I calculate six

conditional means, based on the number of years that children spent in poverty before age six.

On average, each year of early-childhood poverty is associated with an additional 1.2 years of later-childhood poverty (which equals an additional 2.2 years of total exposure to poverty, across the entirety of childhood). As one might expect, children who never experience early-childhood poverty are least likely to experience poverty at older ages; these children can expect to experience an average of 0.3 years in poverty across childhood. By comparison, children who experience poverty for a single year during early childhood can expect to spend an additional 1.4 years in poverty across childhood (equal to 2.4 years of total exposure).

The overall differences are stark. Because children who experience early-childhood poverty have higher probabilities of experiencing later-childhood poverty, this means that early-life exposures are strongly correlated with children's duration of total exposure. Comparing children with zero, three, and six years of early-childhood poverty, these children grow up to experience a total of 0.3, 5.9, and 13.8 years in poverty, on average, across the entirety of childhood.

Although it is possible that this association would attenuate at higher levels of exposure, there remain substantial differences between children who spend a majority of their early years in poverty.

There is a significant amount of persistence in the probabilities of experiencing poverty, across childhood, whereby a child's past exposures to poverty are strongly correlated with their subsequent exposures to poverty. But to what

extent are the outsize associations with early-childhood poverty explained by the cumulative effects of poverty?

I find that the association between adult income and early-childhood poverty is reduced substantially after conditioning on children's subsequent exposures to poverty during later childhood. Table 2.2 presents the results of four linear regressions of adult income. Models 1 and 2 demonstrate that an extra year of early-childhood poverty is associated with a larger reduction in income (–3,600 dollars) than an extra year of later-childhood poverty (–2,684 dollars), net of a host of demographic controls. Models 3 and 4, however, reveal that the total association with early-childhood poverty attenuates considerably after conditioning on children's exposures to later-childhood poverty (–1,557 dollars, when using dummy variables to control for subsequent poverty experiences).

In panel (b) of Table 2.2, I use a mediation approach to show that 45 percent of the consequences of early-childhood poverty operate 'directly' and 55 percent of these consequences are mediated by children's subsequent poverty experiences. In other words, one pathway by which poverty might be shaping children's later-life outcomes is through the increased probabilities of experiencing poverty in the future. These results suggest that there is, indeed, persistence in the rates of poverty, such that a child's early-life experiences shape their levels of exposure in the remainder of childhood. But two questions remain. How much do these cross-age correlations vary at different ages? And to what extent are these cross-age correlations due to the cumulative effects of the initial poverty exposure?

2.8 Discussion

Why do timing dynamics shape the relative consequences of disadvantage? I answer this question by examining a significant finding of the poverty literature, which shows that early-childhood poverty is associated with worse socioeconomic outcomes than later-childhood poverty. Social scientists have generally explained timing effects by emphasizing the unique features of different periods of exposure—which I refer to as the "chronological dimension of timing." An exposure to poverty during early childhood might be more harmful than during adolescence, if the age-specific consequences of poverty are larger in magnitude for young children than for older children. However, there is an alternate explanation for the heterogeneous effects of timing, when the period of exposure is correlated with the total amount of cumulative exposure—which I refer to as the "cumulative dimension of timing." The outsize consequences of early-childhood poverty might be explained by differences in cumulative exposure, if children who experience poverty at a young age have systematically higher rates of poverty during the rest of childhood.

I compare these two theoretical explanations by investigating how differences in the timing of exposure to childhood poverty shape income inequalities in adulthood. I examine a cohort of Americans who can be observed from birth until their thirties, using nationally representative data from the Panel Study of Income Dynamics. To study the chronological and cumulative dimensions of timing, I implement a flexible empirical approach for disentangling the consequences of different dynamic characteristics. This empirical strategy provides a framework for studying temporal patterns across many research contexts.

There are three key findings that contribute to central debates in sociology and the broader social sciences. First, I present evidence of the strong correlation between the timing of childhood poverty and children's cumulative exposure to poverty, across the entirety of childhood. I find that, when a child experiences poverty at a very young age, they are systematically more likely to experience poverty for a longer duration of childhood, compared to their peers who are not exposed to poverty at a young age. These results suggest that the outsize consequences of early-childhood poverty might be a function of children's cumulative exposure to poverty—rather than differences in the magnitude of poverty's age-specific consequences. This is theoretically significant, because cumulative exposures and age-specific consequences point to different explanations for why early-childhood poverty might be associated with worse socioeconomic outcomes than later-childhood poverty. It is, therefore, necessary to disentangle the influence of these two dynamic characteristics.

Second, I develop a flexible empirical approach to compare the relative influence of children's age-specific exposures to poverty and their total exposure to poverty, which I have shown to be strongly correlated. I find that, after controlling for the total length of time that children spend in poverty, the age at which children are first exposed to poverty is not associated with their adult incomes. In other words, early-childhood poverty is associated with worse socioeconomic outcomes because children who experience poverty at a young age spend the longest amount of time in poverty, across the entirety of childhood. Next, I estimate how much of the outsize associations with early-childhood poverty can be attributed to variation in children's cumulative exposure to poverty.

Third, I use a mediation strategy to show that roughly half of the early-childhood poverty association may operate through children's experiences with poverty in later childhood. In other words, half of the total association between early-childhood poverty and adult income is mediated by a child's subsequent exposures to poverty during the remaining years of childhood. These findings underscore the cumulative nature of poverty, whereby an exposure can affect adult outcomes directly and indirectly—through the increased probability of experiencing persistent poverty at older of childhood.

The results of this study have widespread implications for scholars of inequality. By documenting the strong correlation between children's timing and total exposure to poverty, I demonstrated that differences in cumulative exposure can offer a plausible and alternate explanation for the importance of childhood poverty timing. In doing so, I provide a simple tool for social scientists to test whether the cumulative dimension of timing may offer a competing explanation for timing effects—by examining whether there is a correlation with the total amount of exposure to an event, status, or related quantity.

Contrary to a central claim in the study of poverty, I find no evidence to support the sensitive-age perspective, which has emerged as the dominant explanation for why the timing of childhood poverty shapes adult outcomes. Instead, I show that the outsize associations with early-childhood poverty are better explained by the cumulative exposure perspective.

This study advances social science research with contributions that extend beyond the empirical context of poverty. Theoretically, the results of this study point to the dangers of generating theories based on associational evidence and

latent constructs, without directly testing the concepts on which we are drawing inferences. In particular, researchers should be careful not to interpret timing effects as de facto evidence of period-specific explanations.

Social scientists have provided robust evidence about the associations between childhood poverty timing and an array of different outcomes (see Duncan et al. 2017). However, I argue that there are at least two theoretical explanations for the associations that scholars have previously identified. Most studies interpret findings as supporting period-specific explanations—theories that emphasize the unique causes, consequences, and features of the exposure period—or what I call the chronological dimension of timing. However, by itself, the identification of an association with timing is not sufficient evidence to support a conclusion about the sensitive-age perspective, when systematic differences in cumulative exposure can also offer a competing explanation.

Timing effects are commonly attributed to period-specific theories that emphasize the unique causes, consequences, and features of the exposure period. However, there is another perspective that must be considered. When there is a correlation between timing and total exposure, then it is possible that timing effects may be better explained by theories that emphasize the amount of cumulative exposure across a longer range of time. I refer to this perspective as the "cumulative dimension of timing," in contrast to the "chronological dimension of timing" that foregrounds the exact year or age in which something happens. These two dimensions of timing must be considered, empirically and theoretically, because each perspective is associated with a different set of theories and mechanisms for why exposure timing might influence an outcome.

For scholars of inequality dynamics, I propose a flexible empirical approach for directly measuring and modeling dynamic characteristics that may be correlated with one another (because they are dynamics of the same phenomenon). Although this approach was implemented in the context of childhood poverty, scholars can apply this empirical strategy to study the timing, duration, and volatility of any other context (e.g., health events, employment spells, family transitions).

While this study advances the literature, there are limitations for future studies to improve upon. First, I do not formally adopt a causal framework. Therefore, I have been careful to interpret the findings of this study as associational. Although I did not formally test causal pathways, I did provide evidence that challenged one set of theoretical explanations and provided support for another set of theoretical explanations. There is, of course, strong need to identify more proximate causal mechanisms that connect the timing of childhood poverty with adult socioeconomic attainment (see Duncan et al. 2017). Second, this study only explored the logic of poverty's cumulative effects. The goal of this article was to put into the conversation the need to identify, theorize, and provide robust estimates of the cumulative dimension of timing—as an alternative to the period-specific explanations that are typically discussed.

A key take-away of this study is that the outsize harms that are associated with early-childhood disadvantages are not always due to the reasons that we think. In the context of poverty, an early-childhood exposure is associated with worse outcomes—not because poverty is so much more harmful for young children than older children, but because the children who are born into poverty are the

same children who are more likely to experience poverty at age 3, and age 6, and age 9, and age 12.

It stands to reason that we should continue investing in early-life interventions and social programs (see Doyle et al. 2009)—but not because young children are so much more vulnerable to the harms of poverty and older children are better equipped to handle poverty on their own. On the contrary, poverty exposures are harmful at every age (Lichter 1997), and, therefore, our goal should be to reduce the total number of years that children spend in poverty across the entirety of childhood. To be clear, this study actually corroborates the fact that children who are exposed to poverty at a very young age grow up to have the worst socioeconomic outcomes. Children who experience disadvantage at a young age have the highest rates of cumulative disadvantage—and it is this fact that explains the outsize consequences of early-childhood poverty for adult socioeconomic attainment.

2.9 Tables and Figures

All of the tables and figures for Chapter 2 are included on the pages that follow, in the order that they were mentioned in the text.

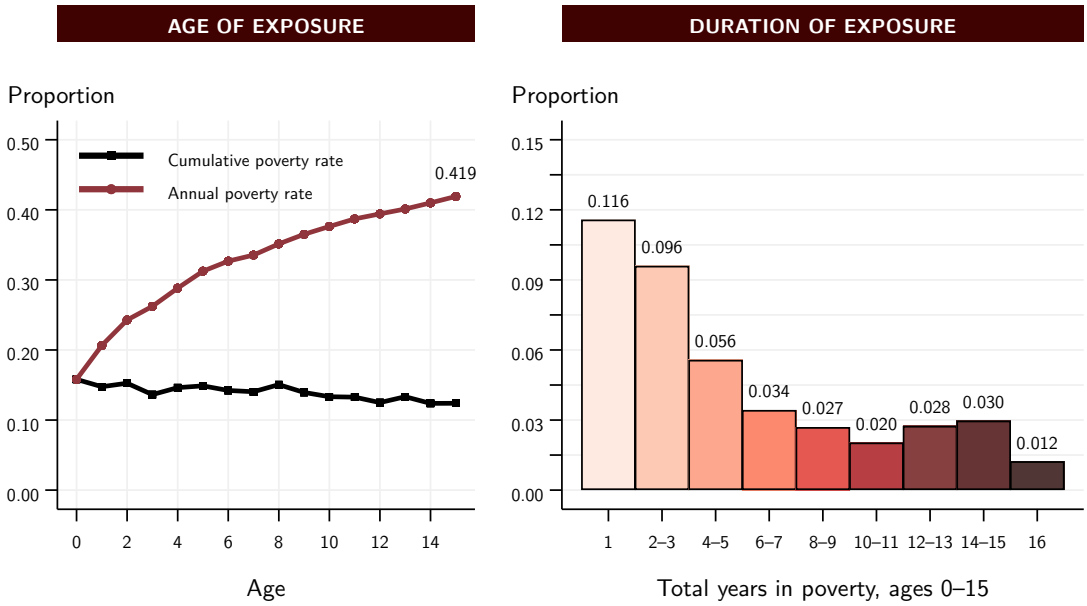


Figure 2.1: Heterogeneity in Children's Poverty Experiences, by Age and Duration of Total Exposure

This figure plots the proportion of all children who experience poverty, (a) at each age; and (b) for different lengths of childhood. In the right-hand panel, the proportion was not displayed for children who spent zero years in poverty (58.1 percent). All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

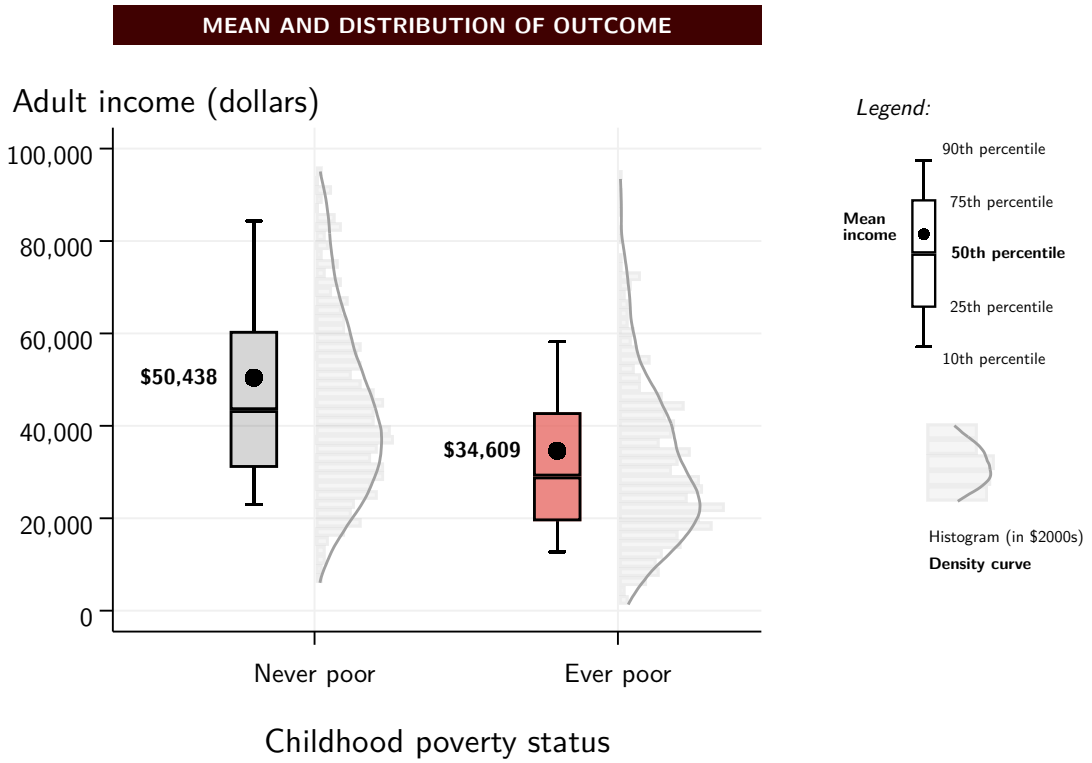


Figure 2.2: Intergenerational Differences in Adult Income, by Childhood Poverty Status

This figure presents the distribution of adult income for two groups: individuals who were never exposed to poverty as children and individuals who experienced at least one year of poverty between the ages of 0 and 15. The black dot (and corresponding dollar amount) represent the mean income for each group. Dollar values represent the individual's average family income, between the ages of 30 and 39, adjusted for taxes and transfers, equivalized for family size, and expressed in 2018 dollars. The box plot represents the group's median and the weighted distribution of income. The histogram and density curve represent the unweighted distribution of income (in $2000 increments); the highest values (above the 95th percentile) are not displayed. Weighted estimates are representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

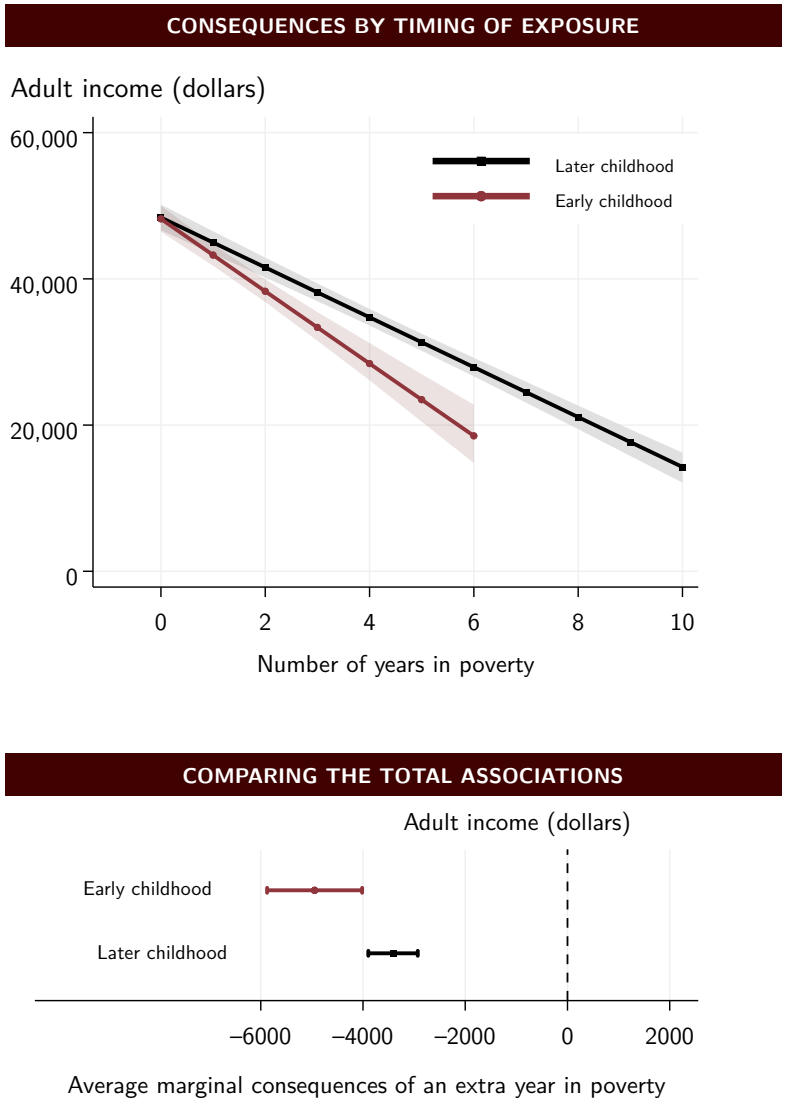


Figure 2.3: The Outsize Consequences of Early-childhood Poverty: Total Associations with Adult Income, by Children's Poverty Experiences in Two Periods of Childhood

This figure displays the estimated associations between adult income and the number of years that children spend in poverty during two periods: early childhood (ages 0 to 5) and later childhood (ages 6 to 15). Predicted values are based on total associations, with shaded areas denoting the 95-confidence interval intervals, based on 1000 bootstrapped samples. In the bottom panel, the corresponding marginal associations are displayed with 95-percent confidence intervals. All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

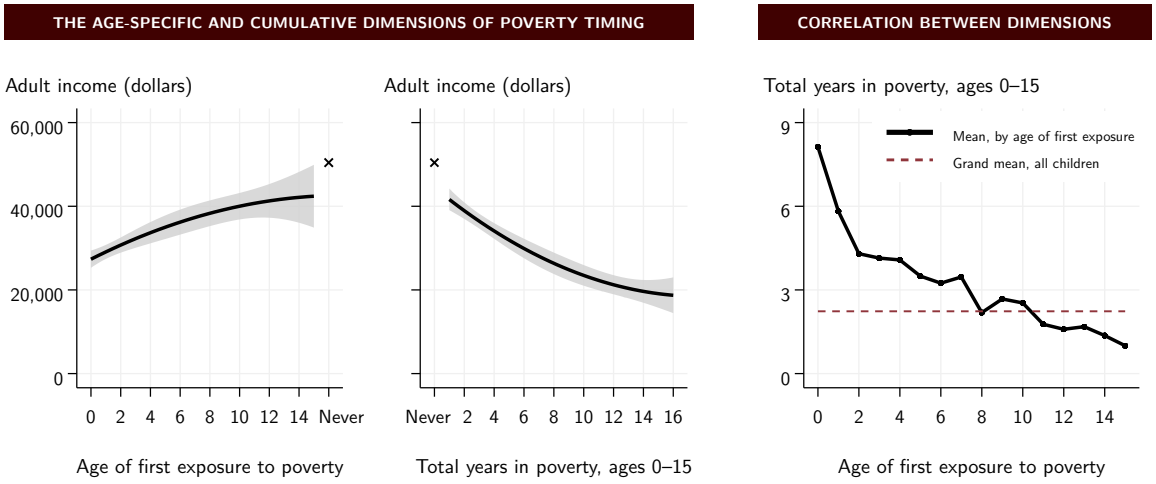


Figure 2.4: Two Explanations for the Outsize Consequences of Early-childhood Poverty: Correlations Between Age-specific and Cumulative Exposures to Poverty

This figure examines two explanations for the outsize consequences of early-childhood poverty, by examining associations between adult income and two dimensions of poverty timing. Panels (a) and (b) use quadratic prediction plot with 95-percent confidence intervals to visualize any nonlinearities. Panel (c) highlights the correlation between the two childhood poverty dynamics by plotting conditional means using observed data and without any modeling assumptions. All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

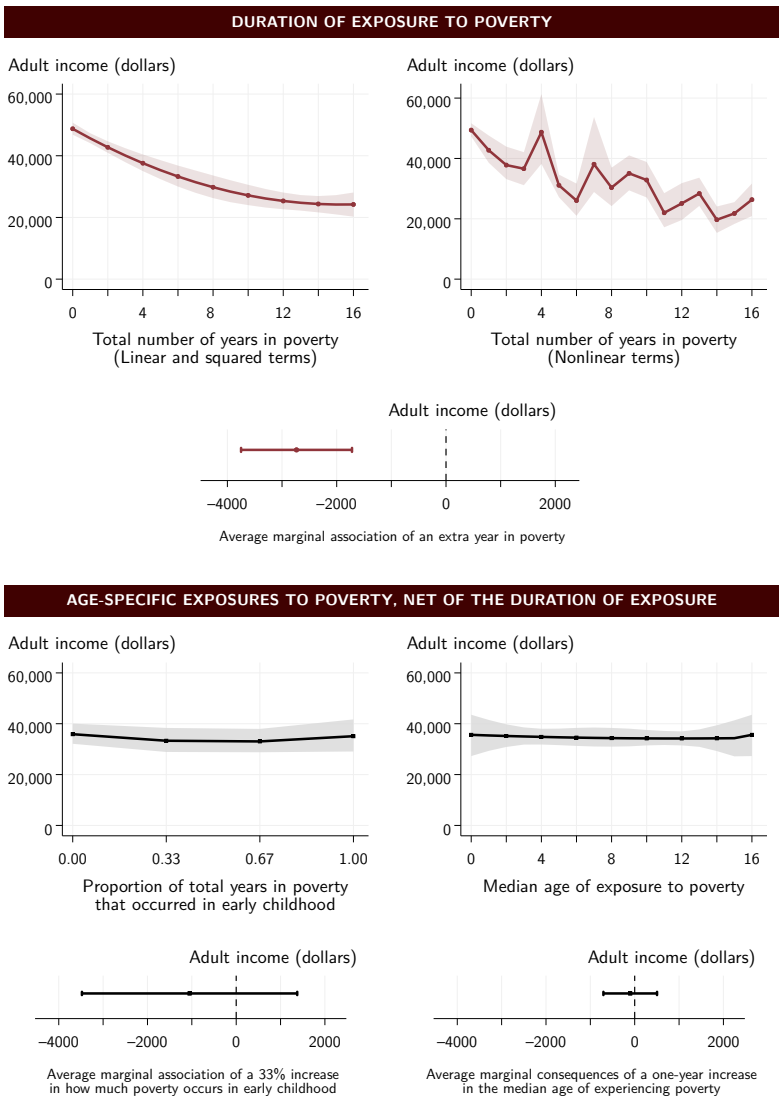


Figure 2.5: Disentangling the Consequences of Age-specific Exposures by Comparing Children with Equal Lengths of Cumulative Exposure to Poverty

In the top panel, three plots display regressions of adult income on the duration of exposure to poverty, (a) using linear and squared terms and (b) using nonlinear terms that do not assume any functional form. The third plot displays the corresponding marginal association (for the linear and squared specification) with a 95-percent confidence interval. In the bottom panel, four plots display regressions of adult income on the age-specific exposure to early-childhood poverty, net of the duration of exposure, (a) using a measure of age-specific exposures based on the proportion of total years in poverty that occurred in early childhood and (b) using a measure based on the median age of exposure to poverty. Below each, there is the corresponding marginal association with 95-percent confidence intervals. Each regression includes several control variables: child gender, race, and birth year; region of residence; and number of siblings. Standard errors were clustered to account for sampling strata and family-level membership. All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

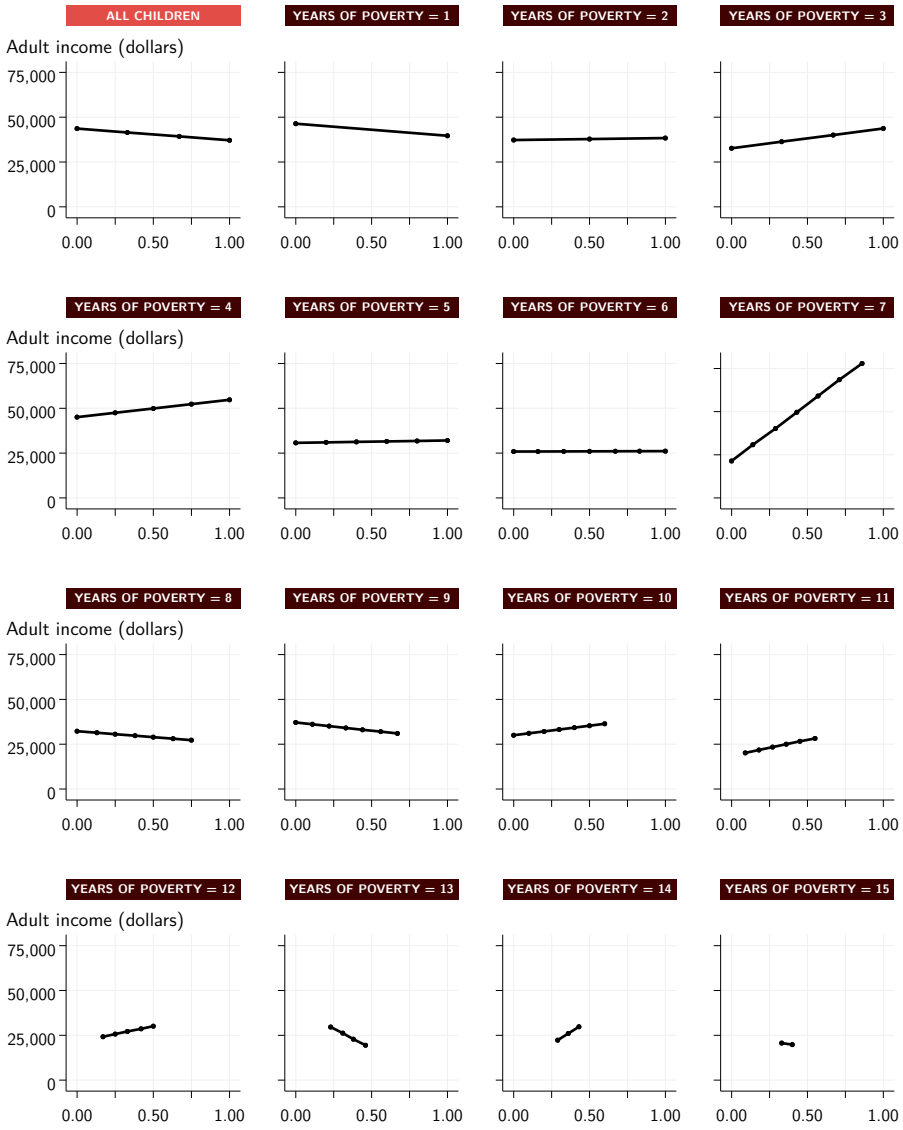


Figure 2.6: Further Evaluating the Influence of Age-specific Exposures to Poverty, Net of Children's Length of Cumulative Exposure: Adding an Interaction Term

This figure plots the predicted values of adult income, which are similar to the estimates presented in panel (b) of Figure 5, except that the current analysis includes interaction terms between the continuous predictor (proportion of total years in poverty that occurred in early childhood) and a series of dummy variables (for each value of the total number of years in poverty). The interaction term allows for different slopes for children who experienced a different number of years in poverty. Each regression included several control variables: child gender, race, and birth year; region of residence; and number of siblings. All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

Table 2.1: The Cumulative Probabilities of Experiencing Poverty in Childhood

	Probability of poverty, at age 6	**Remaining years in poverty, ages 6–15**		**Total years in poverty, ages 0–15**		**Proportion of children**
	%	*M*	*SD*	*M*	*SD*	*%*
Number of years spent in early-childhood poverty, ages 0–5						
0	0.021	0.3	1.0	0.3	1.0	0.688
1	0.146	1.4	2.3	2.4	2.3	0.107
2	0.237	2.7	3.2	4.7	3.2	0.064
3	0.389	2.9	3.4	5.9	3.4	0.028
4	0.598	4.8	4.3	8.8	4.3	0.038
5	0.806	6.0	3.8	11.0	3.8	0.035
6	0.867	7.8	3.3	13.8	3.3	0.041
All children	0.142	1.3	2.7	2.2	4.0	1.000

Note: The Childhood Poverty Matrix, containing the full set of age-specific probabilities of entering poverty at each age of childhood, is available in Appendix Table A.1. [Back to text.]

Table 2.2: Early-childhood Poverty and the Mediating Role of Future Poverty Exposures

PANEL A. Regression of Adult Income on Years in Early- and Later-childhood Poverty.

	Total associations for each childhood period				Early-childhood poverty, controlling for post-treatment exposures			
	Model 1		Model 2		Model 3		Model 4	
	β	SE(β)	β	SE(β)	β	SE(β)	β	SE(β)
Early-childhood poverty, ages 0–5								
Years (linear)	-3,654	537	—	—	-1,619	714	-1,557	728
Later-childhood poverty, ages 6–15								
Years (linear)	—	—	-2,684	287	-2,022	413	—	—
Number of years (ref. 0)								
1	—	—	—	—	—	—	-4,628	3,726
2	—	—	—	—	—	—	-10,007	3,929
3	—	—	—	—	—	—	-11,853	3,471
4	—	—	—	—	—	—	-2,038	3,789
5	—	—	—	—	—	—	-15,975	2,921
6	—	—	—	—	—	—	-15,897	3,128
7	—	—	—	—	—	—	-16,601	-3,690
8	—	—	—	—	—	—	-13,972	4,265
9	—	—	—	—	—	—	-18,162	3,822
10	—	—	—	—	—	—	-18,165	4,304
Controls Included	Yes		Yes		Yes		Yes	
Intercept	51,141	1,989	51,294	2,039	51,613	2,024	52,301	2,350
R-squared	0.093		0.103		0.107		0.112	
N	1,909		1,909		1,909		1,909	

PANEL B. Mediation of Early-childhood Poverty by Children's Future Poverty Exposures.

	Total association	Conditional association	Mediated association	Percent mediated
Early-childhood poverty, with and without post-treatment poverty exposure	-3,654 (-4,541, -2,707)	-1,557 (-2,867, -143)	-2,097 (-2,856, -1,332)	-57.4 (-94.9, -32.9)

Note: All regression estimates were adjusted for several control variables, including child gender, race, and birth year; region of residence; and number of siblings. Standard errors were clustered to account for sampling strata and family-level membership. For each estimate from the mediation analysis, a 95-percent confidence interval was calculated based on 1000 bootstrapped samples. All estimates are weighted to be representative of U.S. children born between 1967 and 1982. N = 1,909 individuals. [Back to text.]

CHAPTER 3

The Depth of Temporal Disadvantage: The Enduring Generational Consequences of Children's Racialized Poverty Experiences

3.1 Introduction

In the United States, children who are born into poverty are more than twice as likely to remain in poverty in adulthood, compared to children who avoided poverty (Parolin et al. 2025). With more than six decades of reliable Census data on year-to-year poverty rates, the share of children who are experiencing poverty has fluctuated significantly, ranging from 3 to 48 percent across different populations (Shrider and Creamer 2023:23–42). Yet, there is one fact that has not changed. No matter how you cut it—regardless of the year, the place, or the

Acknowledgments. I would like to thank Sasha Killewald, Fabian Pfeffer, and Jasmine Simington, for the feedback that they provided me on various aspects of the paper. Earlier versions of this manuscript have been presented at the annual meetings of the Population Association of America and the American Sociological Association. This project has benefited from the generous support of the Social Sciences and Humanities Research Council of Canada (Grant #752-2017-0482), the University of Michigan Library (U-M Library Data Visualization Fellowship, 2024), and the American Sociological Association (ASA Doctoral Dissertation Research Improvement Grant, 2025).

poverty measure—Black children have continuously been exposed to poverty rates that are double and sometimes triple the rates of White children.

Even during unprecedented times, with the temporary expansion of the 2021 Child Tax Credit during President Joseph Biden's COVID-19 response, the child poverty rate fell to historic lows, but the Black-White difference in rates remained stubbornly intact (Shrider and Creamer 2023). So the question becomes, how can we explain the persistence of racialized poverty rates?

Most of the research on this topic falls into one of two theoretical perspectives: individual-level and structural explanations. Individual-level theories emphasize selection processes, parental investments, human-capital differences, and personal or demographic characteristics that are associated with greater "risks" of experiencing poverty (see Brady 2019, for an overview). Structural theories highlight the role of meso- and macro-level contexts—such as segregated housing markets and discriminatory labor practices—which create environments that shape opportunities and systematically advantage (or disadvantage) different groups of people (e.g., Massey 1990; VanHeuvelen and Brady 2022). The literature will frequently focus on the rates of exposure—that is, questions about who is more likely to experience an initial (or recurrent) poverty exposure and the impact that this experience has on their subsequent life chances.

However, I propose another explanation for why racial/ethnic inequalities in poverty have persisted over time. I argue that differences in the *dynamics of exposure* to poverty can explain part of the persistence in Black-White poverty rates. Although many scholars have examined the length (or duration) of

poverty exposures (Alvarado 2016; Li et al. 2018; Wodtke, Elwert, and Harding 2016), I develop an empirical approach for jointly considering population-level differences in the rates and cumulative exposures to poverty.

This paper builds on a simple theoretical insight. Processes of stratification are temporally bounded. That is, an inequality is not possible without some form of differentiation (by status) and a corresponding effect (of the status). However, in most cases, the effect of the status will be highly dependent on time. For example, if there are three unemployed people—who each lost their jobs three days ago, three months ago, and three years ago—they all are experiencing the same status: unemployment. And all of them will contribute equally to the current rate of unemployment. But these three people might be experiencing very different effects of unemployment, which cannot be differentiated without accounting for differences in the length of exposure to their unemployment status.

In this paper, I implement a flexible decomposition approach that allows me to estimate how much the rates of exposure (to a given status) and the length of exposure (to a given a status) are contributing to an overall inequality. I use this approach to theorize (and directly measure) the heterogeneities in how Black and White children are exposed to poverty—in terms of entries and exits, timing, and length of exposure. I refer to these systematic differences as the "racialized experiences with poverty." It is possible that some of our existing estimates of poverty's effects are either under- or over-estimating the consequences of poverty, by not capturing important sources of heterogeneity (Clarke, Kenkel, and Rueda 2018; Kaufman 2013; e.g., Brand and Xie 2010;

Furey 2021). I argue that it may not be sufficient to compare people who have experienced poverty, relative to people who have never experienced poverty—when we are able to capture variation within people's exposures to poverty.

Using the Panel Study of Income Dynamics, I leverage over 50 years of data of Black and White families, to study how much the within-group heterogeneities in children's poverty experiences can explain the between-group inequalities in Black and White economic outcomes. My paper has three main empirical findings. First, I show that the racialized inequalities in childhood poverty are more extreme than we previously realized, using traditional measurement approaches. Although relative poverty rates are twice as high for Black Americans, compared to White Americans—the length of cumulative exposure to poverty for Black children is more than quadruple (4.5 times) that of their White peers (6.8 years versus 1.5 years, on average). Even after restricting the comparison to individuals who experienced poverty as children, Black individuals experience childhood poverty for twice as long as White individuals (8.9 years versus 4.2 years, on average). Second, I find that the marginal associations between childhood poverty and adult income are largest for White individuals, though Black individuals have lower predicted values of income, overall, compared to their White peers. Because the consequences of poverty are larger in magnitude for White children, the difference in racialized associations are somewhat equalizing. However, I also show that poverty predicts less of the variance in adult income for Black individuals—as evidenced by the substantial difference in statistical intercepts between the two groups). This suggests that poverty experiences, alone, have a very strong influence on White economic at-

tainment, whereas Black economic attainment is *also* being influenced by other, non-poverty characteristics. Finally, I develop and implement a flexible decomposition approach that I use to estimate how much of the inequality Black-White adult income can be explained by (1) differences in the rates (or probability) of experiencing any childhood poverty, (2) differences in the length of cumulative exposure to childhood poverty, and (3) differences in the racialized associations between childhood poverty and adult income. I present evidence that differences in how children poverty exposures are distributed explains 14,800 dollars of the overall inequalities in Black-White income. Crucially, more than 90 percent of this finding is being driven by differences in the length of cumulative exposure to poverty—and only 8 percent is driven by differences in the rates of exposure.

My study makes four contributions to the field of sociology. First, I show that children's racialized poverty experiences are more unequal than we previously realized, using traditional measures. Second, I present a partial explanation for why Black-White inequalities in poverty rates persist over time. By jointly estimating the role of children's poverty rates and cumulative exposures, I find that the temporal differences in children's poverty experiences contribute significantly to Black-White economic inequality in adulthood. Third, scholars can use the flexible empirical approach that I developed, in order to differentiate the contributions of many different types of temporal exposure. Finally, my study underscores the importance of theorizing (and directly measuring) temporal exposure, as its own axis of inequality. Although I apply these ideas to the empirical context of racial/ethnic inequality in poverty and income—the

theoretical insights are of relevance to a wide range of sociologists from different subfields. Scholars of gender and work, for example, could apply my approach to study heterogeneity in the effects of occupational sex segregation, by jointly considering the rates of segregation and differences in the timing of when occupation structures were changing in composition. Ultimately, my study presents an empirical and theoretical framework for identifying the unique role that temporal exposures might play across any number of inequality-generating processes.

3.2 Racial/Ethnic Inequalities in American Poverty

In the United States, poverty and racial/ethnic inequalities are highly correlated with one another (Baker et al. 2021). Black Americans, in particular, have higher poverty rates in the United States than any other racial/ethnic group. Although year-to-year poverty rates fluctuate significantly (Parolin and Filauro 2023), these aggregate-level fluctuations have not helped to reduce between-group inequalities. In fact, over the last 60 years, racial/ethnic inequalities in poverty have remained stubbornly consistent (Iceland 2019; Manduca 2018). So, the question becomes, what is contributing to the enduring racialized inequalities in poverty across generations of families?

Most of the research falls one of two theoretical perspectives: individual-level and structural explanations. First, there are numerous studies that explore the individual-level factors that shape whether a person experiences poverty (often referred to in the literature as the "risk" of experiencing poverty). Scholars have explored the roles of education and human-capital differences (e.g., McKernan

and Ratcliffe 2005), marriage and other family characteristics (e.g., Rendall, Weden, and Brown 2022), and parental investments (e.g., Baker 2022a). However, there has been a recent push toward considering structural explanations for how political, legal, and economic contexts create the conditions that create poverty (see Brady 2019; Brady et al. 2017). For example, some studies have examined how structural factors explain the persistence of racial/ethnic inequalities in poverty, such as how geography and impoverished neighborhoods contribute to the persistence of poverty (e.g., Quillian 2003; Sampson 2009). And, more recently, a burgeoning subfield has emerged among sociologists that explicitly demonstrates how contemporary poverty rates can be traced, in part, to the lasting effects of slavery, Jim Crow, and the legacies of historical racism (e.g., Acharya, Blackwell, and Sen 2016; Baker 2022b; O'Connell 2012).

But what if one of the reasons for the generational persistence in poverty can be explained by the dynamics of the actual poverty *exposures* themselves? To evaluate whether this might be a potential explanation, I focus on the intergenerational consequences of childhood poverty, in order to evaluate why Black-White inequalities in poverty are so persistent. For this to be a plausible explanation, (1) there must be systematic differences (or heterogeneity) within children's poverty experiences, and (2) these differences must be associated with future economic inequality.

3.2.1 Temporal Exposures as a Key Source of Heterogeneity for Inequalities in Social Mobility

People who never experienced poverty as children have a lower probability of being classified as "low income" (or below the relative poverty threshold),

compared to people who experienced poverty in childhood (Figure 3.1). White adults who avoided childhood poverty have an 11 percent probability of experiencing poverty in their early 30s. By contrast, Black adults who avoided childhood poverty have a 20 percent probability of spending time in poverty. Of course, this is a large relative difference, but the take-away is that at least 80 percent of both Black and White will continue to avoid poverty in adulthood, if they did not experience it in childhood.

It may not be surprising that, among people who were exposed to poverty in childhood, the early-adult poverty rates continue to be higher for Black adults, compared to their White peers. However, I estimate that the difference in the rate of persistent poverty (i.e., people who will experience poverty in both childhood *and* adulthood) is 34 percent for White individuals and 58 percent for Black individuals (Figure 3.1). In relative terms, this seems to be comparable to the nonpoverty comparison. But the difference of 24 percentage points is an extremely large absolute different. It means that a majority of Black children who spent time in poverty during childhood (nearly two-thirds!) will grow up to continue experiencing poverty as adults.

Why is it that Black Americans fare worse than their White peers, even when we compare groups of people who experienced poverty growing up. This suggests that racial/ethnic differences in the so-called "risks" of experiencing poverty are not sufficient, by themselves, to explain why Black poverty rates are so much higher than White poverty rates.

Therefore, we must move away from *rates* of poverty, in any given year, in favor of a more longitudinal view of a person's lifetime *exposures* to poverty and

other factors that might explain the long-lasting inequalities in poverty by race and ethnicity. In the sections that follow, I begin my reviewing the existing the various theories of poverty mobility. Consequently, I propose an additional perspective for the generational inequalities in poverty, which is rooted in the idea that we have actually been *underestimating* the full extent of how unequal the racialized poverty experiences truly are.

In order to examine whether systematic differences in children's racialized poverty experiences are contributing to the persistence of Black-White economic inequalities, I must use an empirical strategy that can jointly estimate different aspects of children's heterogeneous experiences with poverty. In the section that follows, I outline each step of my empirical strategy, including a flexible decomposition that I developed, in order to examine how systematic differences in children's racialized experiences with poverty contribute to long-standing racial/ethnic inequalities in the United States.

3.3 Empirical Strategy

The objective of this paper is to investigate whether differences in children's racialized poverty experiences can explain the persistence of Black-White economic inequalities. Ultimately, my goal will be to decompose the Black-White inequality in adult income, based on children's rates of exposure (to poverty) and their length of cumulative exposure (to poverty).

To begin, I describe the racial/ethnic inequalities in family income, among Black and White Americans, because incomes are crucial for shaping people's health and life chances (e.g., Duncan et al. 1998; Link and Phelan 1995) and

because differences in income are a frequent object of study in the stratification literature. Therefore, it is an ideal measure for my evaluation of the degree to which children's cumulative exposures to poverty can explain why racial/ethnic inequalities in poverty are so persistent across generations.

My key estimate of interest is the total difference in Black-White incomes, based on the group-specific comparison of mean values. I estimate this total difference to be -18,564 dollars (Figure 3.2). This means that, on average, Black Americans in their early 30s can expect to make nearly 20,000 dollars less than the average White American. Moreover, the figure highlights that the difference in means is not driven by extreme values; at every stage of the income distribution, White people have higher incomes than Black people. For example, White individuals at the 25th percentile have incomes that are higher than Black individuals at the median. Conversely, Black individuals at the 75th percentile have lower incomes than White individuals at the median. There is not a single segment of the income distributions where the racial gap is narrowed.

3.3.1 Estimating the Scale of Black-White Inequality in Children's Poverty Experiences

For my first set of empirical analyses, I reevaluate how much inequality there is in childhood poverty. To do so, I move away from the comparison of poverty rates, in favor of cumulative exposure measures that will illustrate a more-complete picture about how unequal children's experiences with poverty are.

This involves paying special attention to the length of children's poverty exposures, which are occasionally described in the literature—likely due to the

intense data requirements that are necessary for such estimates. However, even when inequality researchers examine the "counts" or "duration of poverty," these inferences tend to be based on short periods of childhood or infrequent repeated measures (e.g., four observations, at birth, age 1, age 4, and age 13—which is common in the fields of developmental psychology and health/medicine). By contrast, I examine children's poverty exposures across a period of 16 years, ranging from ages 0 to 15. The key benefit is greater accuracy in my estimates, but it comes at the cost of reduced sample size and statistical power. For my study, however, the quality of my estimates is paramount, because I am investigating the extent to which children's cumulative exposures might advance our understanding of how racialized poverty experiences persist over time.

Even so, I argue that the comparison of numerical means can sometimes obscure the extreme differences that exist between groups. (What is the difference between "twice as likely" or "three times as likely"? Just a single digit! But the scale of inequality represented by this single digit is easy to miss.) Therefore, in addition to the mean rates of poverty and the mean lengths of cumulative exposure to poverty, I also estimate the complete distribution of children's poverty experiences, looking across all 16 years of childhood. Effectively, I visualize the full length of childhood, as my primary object of interest, as opposed to the share of the population who have experienced poverty for a certain length of childhood (i.e., what is popularly displayed in a histogram). Although histograms have tremendous value, I argue that, in the case of childhood poverty, my unique descriptive approach underscores how unequal children's racialized poverty experiences actually are.

3.3.2 *Estimating the Associations Between Childhood Poverty and Adult Income*

After establishing these differences in how children's poverty experiences are distributed, across the population, I examine the implications for intergenerational inequality. I estimate four sets of linear regressions of adult income on children's cumulative exposure to poverty. All analyses are run separately for Black and White children.[1] By allowing each regression coefficient to vary by race, I am able to avoid any strong assumptions about the impact that poverty being the same for both Black and White children—and can better assess the uniquely racialized experiences that children might have with poverty.

Theoretically, my objective is to study the influence that childhood poverty has on adult income. Empirically, I estimate my key predictor using three key measures: (1) whether a child was exposed to poverty across childhood (any poverty versus no poverty, ref.), (2) the total number of years that a child spent in poverty (treated continuously), and (3) a squared-term of the total number of years that a child spent in poverty, to allow for nonlinearities in the associations with children's later-life incomes.

Equation (3.1) provides an overview of this modeling approach. On the left side of the equation, I am estimating adult income ($Y_{i\boldsymbol{R}}$), for individuals, i, with separate models for each racial/ethnic group, $\boldsymbol{R}$. There are four main coefficients that I obtain from these regressions (i.e., β_0, β_1, β_2, β_3). The first coefficient, $\beta_{0\boldsymbol{R}}$, represents each regression's intercept, which I collect because

[1] All estimates were weighted to be nationally representative of Black and White children born in the United States between 1967 and 1989, and I cluster my standard errors in each regression to account for sampling strata and family-level membership.

major differences in the intercept can mean that there are different underlying theoretical processes across the populations being compared. Each of the next three coefficients represent the associations between adult income and the three key predictors that I outlined earlier.

$$
\begin{aligned}
Y_{i\boldsymbol{R}} \;=\; & \underbrace{\beta_{0\boldsymbol{R}}}_{\text{Intercept}} \;+\; \underbrace{\beta_{1\boldsymbol{R}} Pr(AP_{i\boldsymbol{R}})}_{\text{Rates of poverty}} \\
& +\; \underbrace{\beta_{2\boldsymbol{R}} E(CE_{i\boldsymbol{R}}) \;+\; \beta_{3\boldsymbol{R}} E(CE^2_{i\boldsymbol{R}})}_{\text{Cumulative exposures to poverty}} \;+\; \underbrace{C_{i\boldsymbol{R}}}_{\text{Controls}} \;+ \epsilon_{i\boldsymbol{R}}
\end{aligned}
\tag{3.1}
$$

The first coefficient, $\beta_{1\boldsymbol{R}}$ provides an estimate of the association between adult income and an individual's probability of experiencing any childhood poverty ($Pr(AP_{i\boldsymbol{R}})$), averaged across all individuals, i, for each racial/ethnic group, $\boldsymbol{R}$. The second and third coefficients provide estimates of the associations with the cumulative exposure to poverty ($E(CE_{i\boldsymbol{R}})$), based on the linear term of the total number of years exposed to poverty ($\beta_{2\boldsymbol{R}}$) and the squared term ($\beta_{3\boldsymbol{R}}$), averaged across all individuals, i, and specific to each racial/ethnic group $\boldsymbol{R}$. Finally, the remaining two terms from Equation (3.1) represent a vector of control variables ($C_{i\boldsymbol{R}}$) and the error term ($\epsilon_{i\boldsymbol{R}}$), both of which are averaged across individuals, i, and separately estimated for each racial/ethnic group, $\boldsymbol{R}$.

3.3.3 Decomposing Black-White Income Inequality into the Contributions of Children's Poverty Experiences

Having estimated both the racialized *distributions* and *associations* with childhood poverty exposures, I have the necessary ingredients for decomposing the total difference in Black-White adult income, in order to assess the extent to which differences in children's poverty experiences are contributing to the persistence racial/ethnic income inequality.

In order to accomplish this objective, I developed a decomposition approach that allows me to examine the different aspects of how poverty is *distributed* across the population (i.e., rates, cumulative exposure), as well as how these poverty distributions are *associated* with adult income. My approach is based on the two-fold decomposition, developed by Kitagawa (1955) to examine differences between two rates, which was subsequently expanded to include the decomposition of regression parameters, by Oaxaca (1973) and Blinder (1973).

Ultimately, I decompose the total difference in Black-White adult income, into three main components: the Black-White difference in how childhood poverty experiences are distributed across the two populations (Component A); the Black-White difference in the relative magnitude of the associations between childhood poverty and adult income (Component B); the difference in intercepts and control variables (Component C).

Both components (A) and (B) can be further divided into two subcomponents, differentiating the distributions (and associations) that can be attributed to the rates of experiencing any poverty (which I refer to as: A1, B1) and the length of cumulative exposure (A2, B2). The final term can also be subdivided

into the intercepts, which represent the unexplained variance for children with zero years of poverty (C1) and the variance in adult outcome explained by the means and associations with the control variables (C2).

I formalize this empirical approach in Equation (3.2). The left side of the equation provides the total difference that is being decomposed, where $E(Y)$ represents the expected value of adult income, averaged across each individual, i, within an additional subscript that denotes the racial/ethnic groups that are being compared (i.e., $_{\boldsymbol{B}}$, for Black individuals; and $_{\boldsymbol{W}}$ for White individuals).

$$
\begin{aligned}
\underbrace{E(Y_{i\boldsymbol{B}}) - E(Y_{i\boldsymbol{W}})}_{\substack{\text{Black–White difference}\\ \text{in adult income}}} &= \underbrace{[Pr(AP_{i\boldsymbol{B}}) - Pr(AP_{i\boldsymbol{W}})] * \beta_{1\boldsymbol{W}}}_{\substack{\textbf{A1}\text{: Difference in the distributions}\\ \text{of experiencing any poverty}}} \\
&+ \underbrace{\begin{array}{l}[E(CE_{i\boldsymbol{B}}) - E(CE_{i\boldsymbol{W}})] * (\beta_{2\boldsymbol{W}} + [\beta_{3\boldsymbol{W}} * E(CE_{i\boldsymbol{W}})]) \\ \quad + \ [\ \mathrm{V(CE}_{i\boldsymbol{B}}) - V(CE_{i\boldsymbol{W}})] * \beta_{3\boldsymbol{W}}\end{array}}_{\substack{\textbf{A2}\text{: Difference in the distributions of experiencing}\\ \text{a given amount of cumulative exposure to poverty}}} \\
&+ \underbrace{[\beta_{1\boldsymbol{B}} - \beta_{1\boldsymbol{W}}] * Pr(AP_{i\boldsymbol{B}})}_{\substack{\textbf{B1}\text{: Difference in the associations}\\ \text{with experiencing any poverty}}} \\
&+ \underbrace{\begin{array}{l}\big[\ \beta_{2\boldsymbol{B}} + [\beta_{3\boldsymbol{B}} * E(CE_{i\boldsymbol{B}})]) - (\beta_{2\boldsymbol{W}} + [\beta_{3\boldsymbol{W}} * E(CE_{i\boldsymbol{W}})])\ \big] * E(CE_{i\boldsymbol{B}}) \\ \quad + \ [\ \beta_{3\boldsymbol{B}} - \beta_{3\boldsymbol{W}}] * V(CE_{i\boldsymbol{B}})\end{array}}_{\substack{\textbf{B2}\text{: Difference in the associations with experiencing}\\ \text{a given amount of cumulative exposure to poverty}}} \\
&+ \underbrace{(\beta_{0\boldsymbol{B}} - \beta_{0\boldsymbol{W}})}_{\substack{\textbf{C1}\text{: Difference in}\\ \text{the regression}\\ \text{intercepts}}} + \underbrace{\textstyle\sum_{k=1}^{K}\big[\ \beta_{k\boldsymbol{B}} * E(C_{ki\boldsymbol{B}}) \ - \ \beta_{k\boldsymbol{W}} * E(C_{ki\boldsymbol{W}})\ \big]}_{\substack{\textbf{C2}\text{: Difference in}\\ \text{each control}\\ \text{variable, } k}}
\end{aligned}
\tag{3.2}
$$

On the right side of the equation, there are six Black-White differences that are being evaluated (components A1, A2, B1, B2, C1, C2). Additionally, each

of the parameters from Equation (3.1) are collected and reorganized, mathematically, in order to produce the decomposition. Each component has at least one difference-term (i.e., the comparison of the same parameter across the two racial/ethnic groups). For example, the difference-term for component A1 ($Pr(AP_{i\boldsymbol{B}}) - Pr(AP_{i\boldsymbol{W}})$) represents the Black-White difference in the probability of experiencing any poverty ($Pr(AP)$), across all individuals, i, comparing the probabilities for both Black and White children (i.e., $_{\boldsymbol{B}}$ or $_{\boldsymbol{W}}$).

Every difference-term also has a corresponding 'weight' that it is being multiplied by. This allows the contributions of a particular Black-White difference to be uniquely estimated, by setting the parameter that is not being compared to a single group-specific value. After reordering all of the terms in the equation, so that they each have a difference-term that is being multiplied by its correct group-specific weight, this will yield valid estimates how much the different components are uniquely contributed to the total difference that is being analyzed (i.e., on the left side of the equation).

While the A-components identify the Black-White differences in how children's poverty experiences were distributed—that is, the difference in rates of any poverty exposure (A1) and the difference in cumulative poverty exposure (A2)—the B-components focus on the Black-White differences in the associations between childhood poverty and adult income. Additionally, component A2 estimates the Black-White difference in both the mean length of cumulative exposure to poverty ($E(CE_{i\boldsymbol{B}}) - E(CE_{i\boldsymbol{W}})$) and the variance in in cumulative exposure ($V(CE_{i\boldsymbol{B}}) - V(CE_{i\boldsymbol{W}})$). (The addition of these two difference-terms

means that they could be divided into their own unique subcomponents, if there were analytic interest in examining the variance separately from the mean.)

Following the same logic as the A-components, component B1 provides the Black-White difference in the associations with experiencing any poverty in childhood ($\beta_{1\boldsymbol{B}} - \beta_{1\boldsymbol{W}}$), which is represented by the first predictor, β_1, and component B2 estimates the Black-White difference in the associations with length of cumulative exposure to childhood poverty. The difference-term for component B2 is much longer than the others, because it jointly compares the second and third predictors, β_2 and β_3, representing the linear association with the cumulative exposure to poverty, as well as its squared term. (This is also why the variance terms, $V(CE)$ were necessary to include in this decomposition approach, since the squared.) Finally, component C1 provides the Black-White difference in the group-specific regression intercepts ($\beta_{3\boldsymbol{B}} - \beta_{3\boldsymbol{W}}$), and component C2 provides the Black-White difference in the means and associations of the entire set of control variables.

In the results section, I focus mostly on the analysis of the A-components in the decomposition, for both methodological and theoretical reasons. Methodologically, the distributions of children's poverty experiences are well-specified (i.e., components A1 and A2: the mean difference in poverty rates and cumulative exposures), whereas the regression terms are more sensitive to analytic decisions regarding the reference categories selected for measures of poverty and for each of the control variables. For example, the regression intercept will be informative, as a measure of unexplained variance in the adult income, among children with zero years in poverty. Theoretically, the main objective of

my study is to investigate how the unequal distributions of childhood poverty have contributed to the persistence of racialized inequality in adult income.

3.4 Data and Sample

In order to estimate Black-White differences in the intergenerational persistence of poverty, I require data that features (*i*) repeated measures of income and (*ii*) observations for at least two generations of the family members. I use the Panel Study of Income Dynamics (PSID), because of its unique features as the world's longest-running longitudinal household survey, which began in 1968 with a nationally representative panel of more than 5,000 families in the United States. Importantly, for this study, the PSID has interviewed the same groups of children (and their families) for more than 50 years—following children even after they leave the parental home to form their own independent households. The specific data file that I used to construct my sample comes from the PSID's Social, Health, and Economic Longitudinal File (PSID-SHELF), due to its harmonized socioeconomic measures and multigenerational data structure (Daumler et al. 2025).

I have three inclusion criteria for my analytic sample. (1) My main population of interest comprises children who were born between the years of 1967 and 1989.[2] (2) Because the central focus of this study is to examine associations

[2]I restrict the sample to children born in 1967 or later to ensure that I do not miss any observations of child income after a child is born (given that the 1968 survey wave asks families about their income in the preceding year). Additionally, I only include children who were born in 1989 or earlier, because the youngest birth cohort will experience their 15th birthdays in 1997, when the PSID switches from annual to biennial data collection.

with the cumulative exposure to childhood poverty, I require that children be observed annually for their entire childhoods—every year, between the ages of 0 and 15. Although it is a strong requirement, this ensures that I have high-quality estimates of cumulative exposure to childhood poverty, although it is at the expense of statistical power. Finally, (3) I measure children's adult income during their late-20s and early-30s—specifically, between the ages of 27 and 32. I require my sample members to be observed for at least two out of the three waves (following the PSID's switch to biennial interviews).

This culminates in a final analytic sample of 3,488 respondents, for whom I can observe their entire childhoods and assess their eventual outcomes as adults. In total, my sample included 2,057 White children; 1,278 Black children; and 153 children who were identified as belonging to another racial/ethnic group. Due to their small sample size, individuals who belong to another racial/ethnic group are not included in my primary analytic comparisons (though supplementary analyses were run on the full population of children, with and without this subsample included). Therefore, all analyses within this manuscript are based on the final analytic sample of 3,335 Black and White children. Additionally, due to the PSID's oversample of low-income families, half of my analytic sample (1,750 respondents) were exposed to at least one year of poverty in childhood, which is important for my analyses of variation in the dynamics of poverty.

Next, I construct a comprehensive set of measures for income and poverty status. For this study, I calculate each person's mean value of income when they are in their thirties. I use an equivalized measure of disposable family income,

expressed in 2023 dollars, averaging across all available observations between the ages of 27 and 32.[3] Following the recommendation of Brady et al. (2018), I use a relative measure of poverty, by calculating a poverty threshold that is 50 percent of the median income in each year (using the same equivalized measure of disposable family income). When a child's family income falls below this threshold, they are coded as having experienced poverty during that particular year.

I assess children's outcomes during their thirties—using all available observations between the ages of 27 and 32. I examine mean adult income as the study's primary outcome. Estimates of mean adult income may have less measurement error than estimates of adult poverty rates when my sample enters their late-20s and early-30s. In short, when there are only a small number of observations available, there will be a strong underestimate of the rates of adult poverty,[4] whereas Brady et al. (2018:336) show that averaging across 2 to 5 years of income observations explains most of the variation in permanent income.

Finally, in addition to running analyses separately for Black and White children, I add control variables that precede a child's birth, in order to estimate partial associations between childhood poverty exposures and adult income. The current set of analyses feature two immutable characteristics that influence

[3]First, I calculate each family's post-tax and post-transfer income (as opposed to individual earnings, individual income, or pre-tax family income). Second, I equivalize income for family size (by dividing income by the square root of the number of people in the family unit). Finally, I adjust for inflation, using the Personal Consumption Expenditures Price Index, and income values are expressed in 2023 dollars.

[4]Because longer periods of observation (e.g., a 16-year interval, commensurate with how I examine childhood) will always yield a higher prevalence of poverty than a shorter period of observation (e.g., a 5-year interval), particularly because a large number of families experience poverty for only a single year (see Figure 2.1, from Chapter 2).

a person's adult income and precede the childhood poverty exposures. These control variables include: child gender (female versus male, ref.); and mean-centered child birth year (treated continuously).[5]

3.5 The Scale of Inequality in Children's Racialized Poverty Experiences

It is true that Black individuals are much more likely to spend time in poverty, during childhood, compared to their White peers. Across the total population of American children (born between 1967 and 1989), Black children were exposed to poverty at twice the rate of White children (Figure 3.3). However, it is essential to interpret the absolute probabilities that are being compared, in order to understand the scale of inequality. Whereas one-in-three of White children experienced poverty (36 percent), three-out-of-every-four Black children spent at least one year of poverty in childhood (75 percent).

Of course, these differences in the rates of exposure likely contribute to between-group differences in adult income, but there is considerable heterogeneity that is possible, whereby one child might spend a single year in poverty, as opposed to another child who spends the majority of childhood in poverty.

[5] Previous versions of this paper included a wider array of child and parent characteristics—such as (a) birth weight, (b) mother's and father's years of education, (c) parents married at birth, and (d) lived with both birth parents at birth. However, a 'causal' analysis of poverty is tricky—because there is a fine line between a confounding variable and overcontrolling for factors that are jointly related with poverty. For example, a parent's unemployment status might technically precede (and cause) the subsequent poverty exposure—but what would it mean to estimate a causal effect of poverty *status*, net of losing your income—or net of experiencing labor-market discrimination, or net of the foreclosure on your home? It is not just the status that we are trying to measure—it is the full experience of disadvantage and all that it entails.

Both of these children would be said to have experienced childhood poverty. On the other hand, the consideration of the rates of poverty is important, because of the unique attributes shared by children who were never exposed to poverty.

Inequalities become even more extreme, when we shift from rates to the cumulative exposure to poverty (i.e., the second column of Figure 3.3). Across the entire population, Black children are exposed to poverty for more than four times higher than the length of time that White children spend in poverty. On average, Black children experience 6.8 years in poverty (more than 40 percent of childhood), which is several times larger than the 1.5 years that White children spend in poverty (slightly less than 10 percent of childhood). However, the top two panels of Figure 3.3 comprise unconditional estimates that include children who never experienced childhood poverty. The story changes somewhat when we remove the children who spent zero years in poverty—and condition on having experienced poverty for at least one year of childhood.

Comparing children who experienced at least one year in poverty, we see that the Black-White inequality in cumulative exposure reduces from a 5.3-year difference (or a difference of 450 percent, in relative terms) to a 4.7-year difference (or 210 percent). This is a function of having 'equalized' the rates of poverty, by conditioning on ever having experienced childhood poverty.

However, despite the reduction from 'quadruple' to 'double', the Black-White inequality in the cumulative exposure to poverty remains large. Black children who are exposed to poverty, on average, spend more than half of their

childhoods in poverty (8.9 years). By contrast, White children who are exposed to poverty spend one-quarter of their childhoods in poverty (4.2 years).

Notably, the failure to consider the length of cumulative exposure would have obscured the full scale of the inequality within the population of children who experienced poverty. In other words, the rates alone would not have captured the full amount of variation in children's later-life outcomes.

Before moving from distributions to the estimates of associations with childhood poverty, I provide a final illustration of the differences in how the racialized poverty experiences are distributed. In Figure 3.4, I invert the histogram to visualize the full scale of the temporal inequalities, among Black and White children who experienced at least one year of poverty. Rather than display the proportion of children who experience different lengths of cumulative exposure to poverty, I display a representative sample of 50 childhoods, each representing two percent of the population of Black and White children, respectively. Each horizontal bar represents 16 years of childhood, and the segments that are shaded black represent how many years of childhood were being spent in poverty, and the segments that are shaded red represent how many years of childhood were spent outside of poverty.

The inequalities in childhood poverty are stark. The distributions of the cumulative exposure to poverty are even more extreme when we examine the full distribution of childhood poverty experiences.

For White children, it is clear that the vast majority has experienced poverty for less than half of childhood (81 percent), with most experiencing fewer than three years in poverty. For Black children, the opposite is true. A majority

of Black children experienced poverty for more than half of childhood (57 percent). At the extremes, a sizable 12 percent of Black children spend the entirety of their childhood in poverty—whereas next to no White children were exposed to constant poverty (Figure 3.4).

Altogether, there are significant inequalities among Black and White children that are not captured by simple rates or probabilities alone. I argue, first, that we underestimated the inequality in children's poverty experiences. These temporal differences offer an additional axis of inequality that researchers can (and should) study, if their goal is to examine between- and within-group differences. Failure to account for such a large source of heterogeneity might lead to the underestimate of associations that are unduly being averaged across groups of people with very different temporal exposures. Second, given the scale of these newly unmasked inequalities, I argue that the cumulative exposures to poverty might offer a partial explanation for the persistence of racialized inequalities in poverty.

3.6 Racial/Ethnic Differences in the Associations Between Childhood Poverty and Adult Income

Next, I estimate the magnitude of the associations between children's exposures to poverty and their later-life adult incomes. In Figure 3.5, I display the estimates of adult income, for Black and White children, by the total length of cumulative exposure to poverty. Linear regressions were run separately for each racial/ethnic group to ensure that the model captures the racialized differences in the temporal exposures to poverty. Although the magnitude of the association

attenuates at the highest number of years spent in childhood poverty—the direction of the association is consistently negative, indicating that an additional year of poverty is associated with a lower level of income attainment. On average, the marginal association of an extra one year in poverty is associated with a 1,500-dollar income loss.

Perhaps the most surprising finding is that the magnitude of the negative association between childhood poverty exposures and adult income is larger for White children than Black children. At first glance, this might suggest that White children are experiencing a more-pronounced income loss—from spending an extra year in poverty—compared to their Black peers. If true, this reversal in the inequalities in associations with poverty would have an equalizing effect on Black-White income inequalities. In other words, if the Black curve were as steep as the White curve, then Black Americans would have even lower incomes than they presently do. But is that the whole story? That is, can we really conclude that the length of cumulative exposures to poverty are more harmful for White children than Black children? Or is there more going on?

Figure 3.6 displays the exact same income penalties to poverty that were displayed in Figure 3.5, except instead of associations, I am displaying the overall predicted values of adult income. In statistical terms, this means that the regression intercept is being reintroduced, which is visible based on the large gap between the two curves for children who never experienced any years in poverty. Although Figure 3.5 provides a better comparison of the differences in the magnitude of the association (i.e., the slopes of the curve), Figure 3.6 offers a fundamental reinterpretation of the differences between the associations, by

combining the associational estimates with the residual factors. Because the regression of adult income for Black children has a much larger intercept, compared to the regression for White children, this suggests that there are either additional unobserved factors that predict Black children's income attainments or that these factors are more highly associated with Black children's outcomes.

Another noteworthy feature of the predicted values displayed in Figure 3.6 is that there is a clear convergence of the two curves at the maximum lengths of cumulative exposure to childhood poverty. This suggests that, regardless of the difference in intercepts, Black and White children who experience more than half of their childhoods in poverty tend to have very similar income attainments.

This could mean that the difference in the slopes is more of a story of 'affluence'—or the extreme differences between Black and White children who were not exposed to poverty, and these differences are more negligible for children who experience the most extreme exposures to poverty.

3.7 Generational Persistence of Racial/Ethnic Inequalities in Poverty

Having established the *distributions* and *associations* for children's poverty exposures, both in terms of the rates of any poverty and the length of cumulative exposure to poverty, I implement a decomposition approach to examine the relative contributions of the different aspects that children's poverty experiences have on the total difference in Black-White incomes.

Table 3.1 displays the results of the decomposition analysis. On average, the entire group of Black children have a mean income that is 18,564 dollars

lower than the mean income of White children. This is the key quantity of interest that I will disaggregate into decomposed components. There are three take-aways from this set of results.

The first take-away is that the Black-White difference in the distributions of childhood poverty (Component A) have the largest contribution to the overall inequality in adult income. This makes sense, given the extreme differences that we saw in *both* the rates of ever experiencing childhood poverty *and* the length of cumulative exposure to poverty. In fact, I find that differences in children's poverty exposures are contributing -14,937 dollars to the total difference in Black-White incomes (Table 3.1). Another way to think about this: if you could somehow artificially set Black children's poverty rates and cumulative exposures to be the same as their White peers, the racial/ethnic inequality in income would be reduced by three quarters (to approximately -3,600 dollars).

The second key take-away is that, all together, the differences in the regression associations and control variables (Components B and C) explain -3,626 dollars in the total difference in mean adult income between Black and White individuals. I suggest caution in interpreting the associations (Component B) separately from the regression interpret (Component C1), due to the sensitivity of these decomposed quantities to analytic decisions regarding each variable's reference category. Instead, we can jointly consider the contribution of the regression and control variables, collectively, as the amount of variance that is not explained by the distribution of children's racialized poverty experiences.

Finally, the third key take-away is about understanding how much of the difference in poverty's distributions are driven by the traditional measure of

poverty rates, versus the value added by this study's measure of the cumulative exposure to poverty (Panel 2). Less than 20 percent of the Black-White adult income that is explained by the distribution of poverty across the population (-14,937 dollars: Component A) can be attributed to the difference in poverty rates (-1,123 dollars: Component A1). In other words, more than 80 percent of the racialized inequality in adult income is driven the differences in the cumulative exposures to poverty (-13,814: Component A2).

3.8 Discussion

In this study, I show provide new estimates of the scale of racial/ethnic inequalities in childhood poverty—and I suggest that these systematic differences in the temporal exposures to poverty are partially responsible for the generational persistence in Black-White economic inequality. I leverage over 50 years of data using the Panel Study of Income Dynamics, to decompose the inequalities in family income between Black and White adults. This study shows that temporal exposures may be an axis of inequality that can explain how inequalities are produced and reproduced over time. There are three key take-aways from the empirical results of my study.

First, the racial/ethnic inequalities in poverty are more extreme than we previously realized. I find that Black-White differences in the rates of poverty exposures are half the size of the Black-White differences in the length of cumulative exposure to poverty. That is, Black children experience rates of poverty at *twice* the rate of White children, but they experience poverty for *four times* longer than children, on average. When we condition on having been ex-

posed to childhood poverty, the Black-White inequality in the number of years spent in poverty shrinks—but it remains twice as large. Using traditional rate-based measures alone, scholars risk underestimating the amount of inequality in childhood poverty.

Second, I examine the associations between childhood poverty and adult income—and I identify two findings, which I argue must be interpreted in concert with one another. (1) The consequences of childhood poverty were larger for White individuals than Black individuals. However, (2) Black children's poverty exposures also explained much less of the variance in their adult incomes, compared to White children. This suggests that there are other factors at play that shape Black adult incomes, aside from childhood poverty—and these factors either do not affect White individuals or they have a smaller effect. These findings should be interpreted, in conjunction with research on the continued effects of historical and contemporary racism on the lives of Black American (Adames 2023; Baker and O'Connell 2022; Katznelson 1996).

Third, using an original decomposition approach, I find that the inequalities in how childhood is distributed across the population have a significant impact on the total difference in Black-White adult income. In fact, when I differentiate two aspects of children's poverty experiences—the rates of exposure and the length of cumulative exposure—I find that differences in temporal exposures are a major driver of racial/ethnic inequalities in income. Moreover, differences in the rates of exposure have a much smaller impact on Black-White adult income. These findings underscore the sociological significance of studying differences

in the rates (or probabilities) of experiencing a particular inequality, when there are significant differences in temporal exposure.

There are two limitations that future research could address. First, this study focuses on comparing the rates and cumulative exposure to poverty, but subsequent studies might consider examining additional dynamics of poverty. For example, the length of exposure could be correlated with, caused by, or moderated by other dynamics, such as the depth of poverty. Second, the analytic sample that I used had a fairly conservative inclusion criteria (e.g., requiring an income observation from every year of childhood, ages 0 to 15). Future research might benefit from testing (and validating) whether a relaxation of the inclusion criteria produces similar results, as well as sample weights that adjust for the probability of sample inclusion.

Ultimately, my findings underscore that temporal exposures should be considered its own axis of inequality. Methodologically, scholars can use the flexible empirical approach that I developed to differentiate the rates of inequality from the cumulative exposures to inequality. Theoretically, I provide a framework for identifying the unique role that temporal exposures play within an inequality-generating process. While I applied these ideas to the empirical context of Black and White economic inequality, the empirical and theoretical approach that I developed can be extended to a number of different topics and empirical contexts.

By expanding our understanding of children's racialized poverty experiences—to jointly estimate the role of children's rate sand cumulative exposures to poverty—I show that inequalities in childhood poverty are

more extreme than we realized, without considering the length of cumulative exposures. I argue that these inequalities in temporal exposures offer a key explanation for how racial/ethnic inequalities in poverty remain persistent across generations.

3.9 Tables and Figures

All of the tables and figures for Chapter 3 are included on the pages that follow, in the order that they were mentioned in the text.

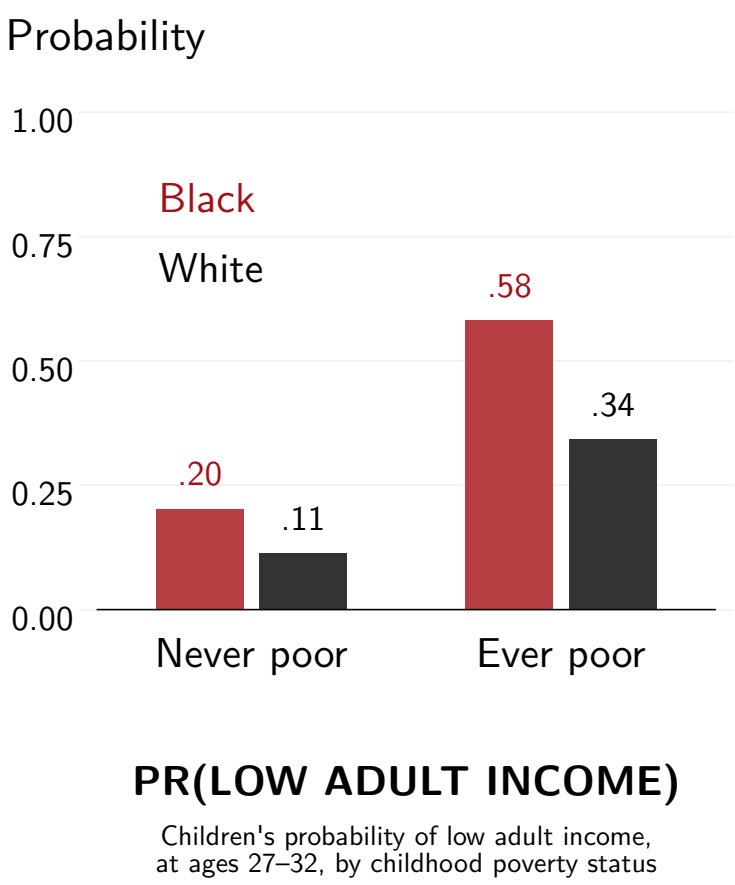


Figure 3.1: Racial/Ethnic Differences in the Rates of Intergenerational Poverty Mobility

Estimates of the unconditional probability of Black and White adults reporting a family income that is below the relative poverty threshold (i.e., 50 percent of the median family income). Probabilities were calculated separately by racial/ethnic group and by childhood poverty status (i.e., experiencing at least one year of childhood poverty). These probabilities do not condition on any other characteristics. All estimates are weighted to be representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

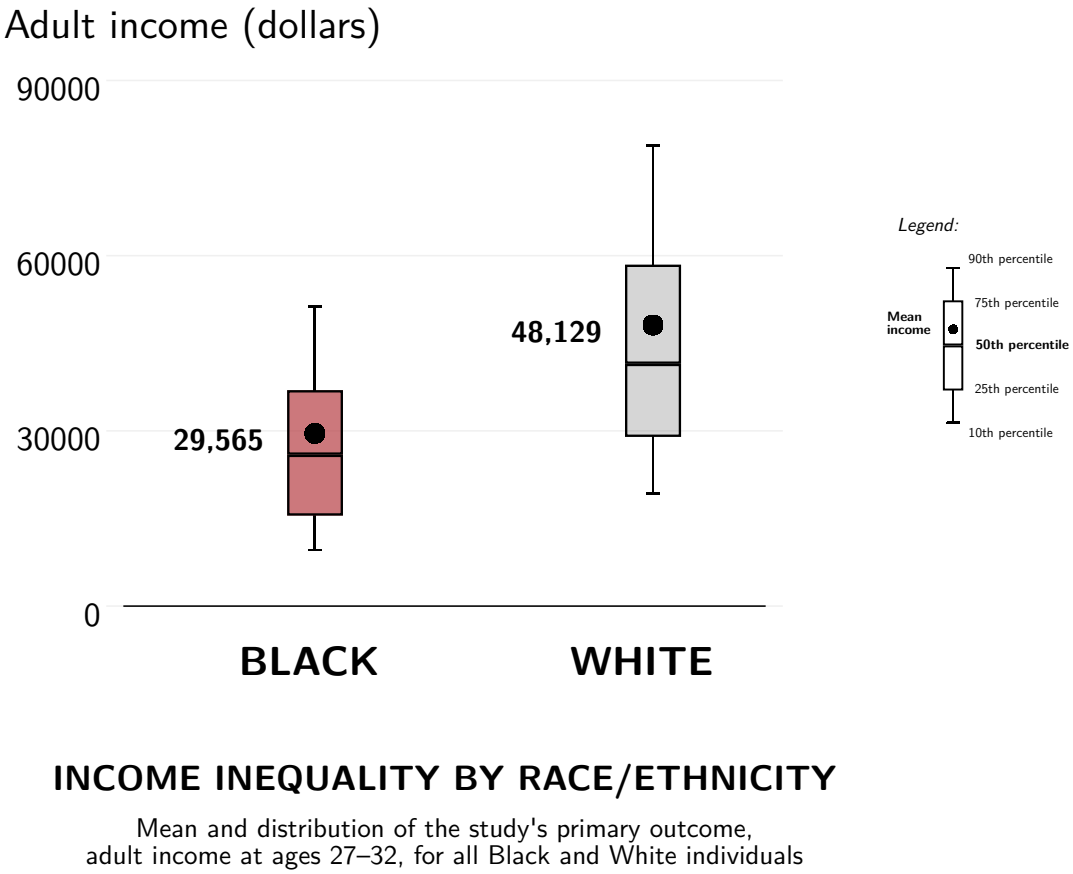


Figure 3.2: Racial/Ethnic Inequality in Adult Income

Estimates of the unconditional mean and distribution of family income, for Black and White adults, at the ages of 26 to 32. Predicted values were calculated separately by racial/ethnic group, and they do not condition on any other characteristics. Weighted estimates are representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

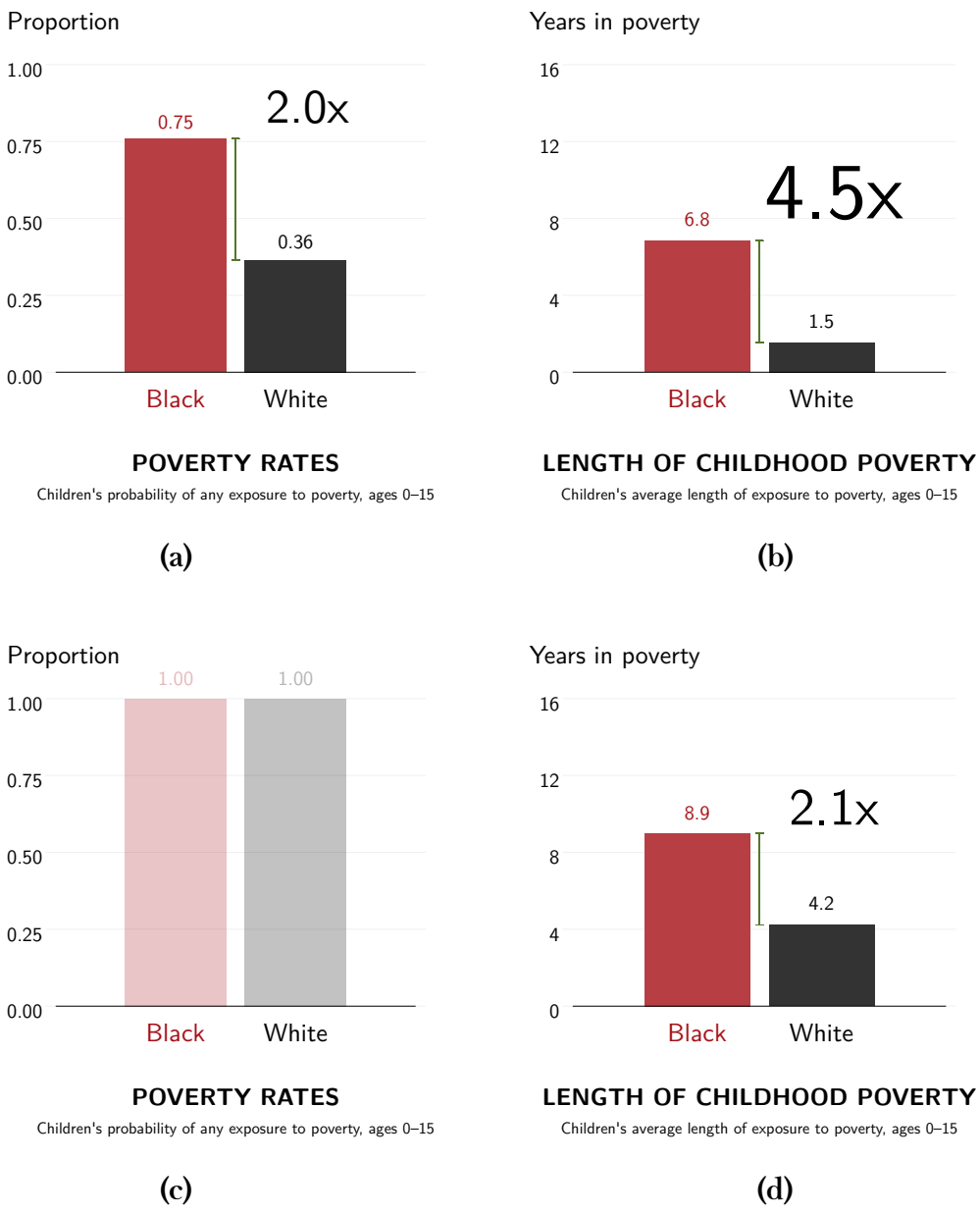


Figure 3.3: Racial/Ethnic Differences in the Rates and Length of Childhood Poverty

Panels (a) and (b) display unconditional proportions and years in poverty, respectively. These predicted values were calculated separately by racial/ethnic group, and they do not condition on any other characteristics. Panels (c) and (d) provide the corresponding conditional proportions and years in poverty, among individuals who experienced at least one year of poverty in childhood. This explains why panel (c) displays two bars with poverty rates of 1.0—because the estimates in panels (c) and (d) condition on an exposure to poverty in childhood. All estimates are weighted to be representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

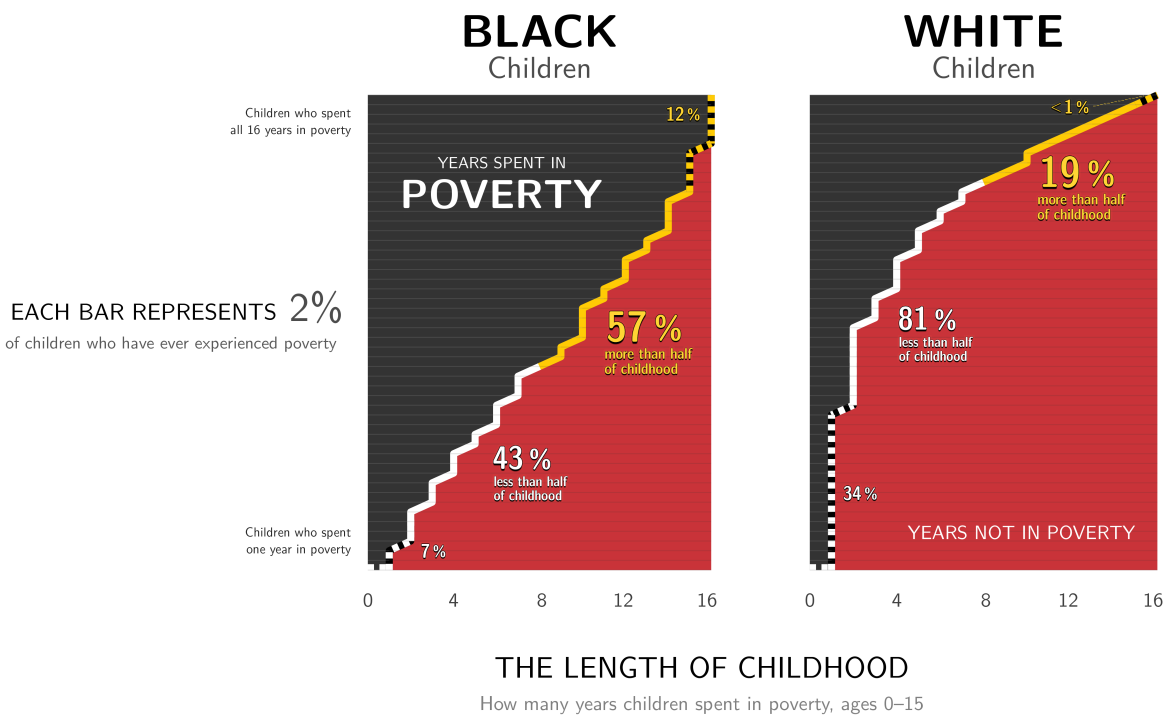


Figure 3.4: The Full Distribution of Children's Racialized Poverty Experiences

This figure visualizes the complete length of childhood, as the primary object of interest, as opposed to the share of the population who experienced poverty for different lengths of childhood. There are 50 horizontal bars, ranging from 0 to 16. Each horizontal bar represents the complete length of childhood for two percent of the population: Black and White children who have been exposed to at least one year of childhood poverty, respectively. The portion of the horizontal bar that is shaded black represents the number of years that were spent in poverty, and the portion shaded red represents the number of years that were not spent in poverty. Horizontal bars are ordered (bottom to top), from the shortest poverty exposures to the longest poverty exposures. The white dividing line, in the middle of the black and red shaded portions, represents the share of children who spent less than half of their childhoods in poverty, and the yellow dividing line represents the share of children who spent more than half of their childhoods in poverty. Each dividing line also has a dashed segment, which represents the share of children who spent only one year in poverty (white-dashed) and the share of children who experienced poverty for their entire share of childhood (yellow-dashed). All estimates are weighted to be representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

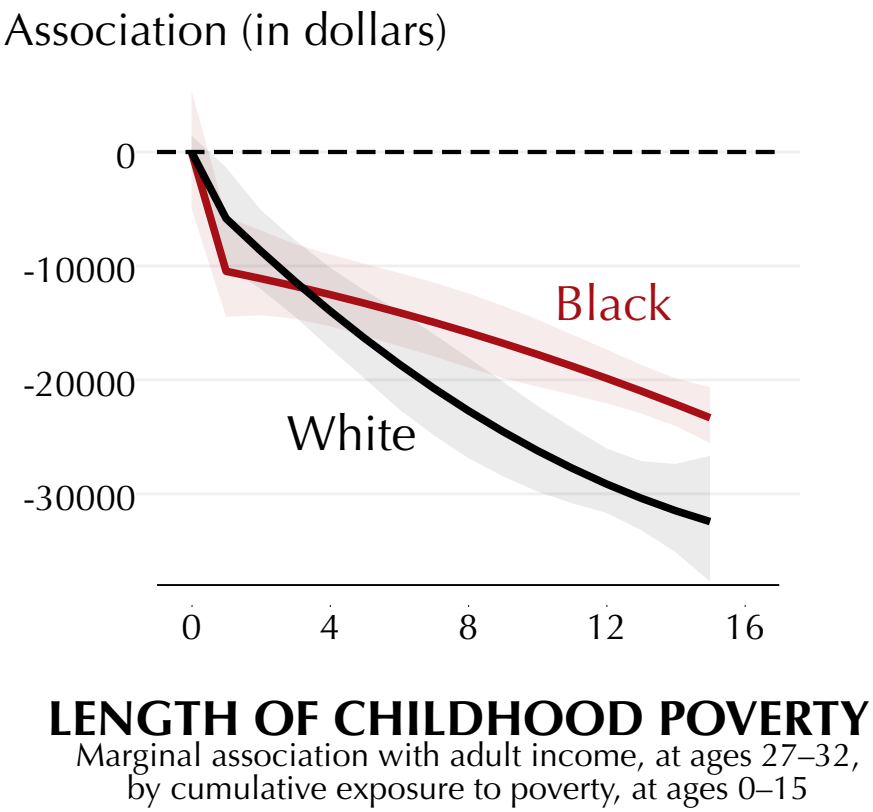


Figure 3.5: Racial/Ethnic Differences in the Associations Between Childhood Poverty and Adult Income

This figure displays the partial associations for the same estimate, adjusting for a series of individual- and parent-level characteristics at baseline. Control variables include: gender, birth year, resides in the South, number of siblings, birth weight, mother's and father's education at birth, mother's and father's age at birth, parents' marriage or cohabitation status at birth, and coresidence with both birth parents at birth. Standard errors were clustered to account for sampling strata and family-level membership. All estimates are weighted to be representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

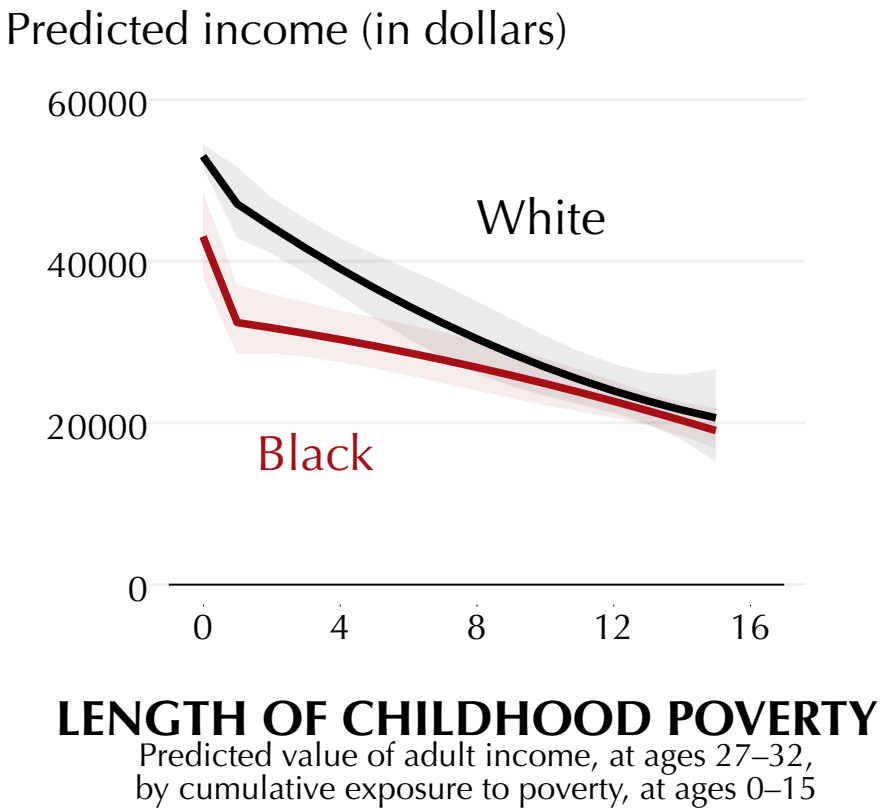


Figure 3.6: Racial/Ethnic Differences in the Predicted Values of Adult Income, by Children's Poverty Experiences

This figure displays the unconditional estimates of adult income, across different lengths of exposure to childhood poverty. These predicted values were calculated separately by racial/ethnic group, and they do not condition on any other characteristics other than the probability of experiencing childhood poverty (ever experience versus never experienced poverty) and the length of total exposure to poverty (number of years). These estimates are derived from the same linear regression used in Figure 5, panel (a), but Figure 6 reintroduces the regression intercepts. The difference in the intercept, where childhood poverty is equal to zero, represents the Black–White differences in the amount of variation in adult income is explained by all other factors other than childhood poverty. Standard errors were clustered to account for sampling strata and family-level membership. All estimates are weighted to be representative of Black and White U.S. children born between 1967 and 1989. N = 3,335 individuals. [Back to text.]

Table 3.1: Decomposition of the Black-White inequality in adult income by children's rates and cumulative exposure to poverty

	Decomposition of the overall adult income inequality	
	Black – White	
	Dollars	Percent
Explained by the distributions of childhood poverty:		
Difference in poverty rates, means (Component A1)	-1,123 (-3,467, 1,527)	6.0
Difference in cumulative exposures, means (Component A2)	-13,814 (-21,154, -6,931)	74.4
Sum of all contributions from distributions (A1+A2)	-14,937 (-19,878, -9,836)	80.5
Unexplained by the distributions of childhood poverty:		
Difference in poverty rates, associations (Component B1)	-5,334 (-12,705, 1,912)	28.7
Difference in cumulative exposure, associations (Component B2)	11,962 (2,835, 21,579)	-64.4
Difference in intercepts, at zero years in poverty (Component C1)	-6,029 (-14,451, 2,926)	32.5
Difference in controls, means and associations (Component C2)	-4,225 (-11,306, 2,710)	22.8
Sum of all regression coefficients and controls (Components B1+B2+C1+C2)	-3,626 (-9,543, 1,685)	19.5
Total difference in mean adult income by race/ethnicity	-18,564	100.0

[Back to text.]

CHAPTER 4

The Cumulative Value of Family Origins: Cohort Change in the Intergenerational Basis for Wealth Inequality

4.1 Introduction

Wealth inequality is one of the defining social problems of our time. And, for some people, wealth inequalities may be getting worse, with scholars finding that families are accumulating lower levels of wealth, today, than they were several decades ago (see Fry 2019; Gale et al. 2021; Gruijters, Van Winkle, and Fasang 2023; Myers, Lee, and Simmons 2020; Mykyta 2012). However, there are major heterogeneities across the distribution of wealth. In their study of cohort change in the total net worth of 'millennials' and 'baby boomers', Gruijters and colleagues (2023) find major differences across the wealth distribution, which show that, at equal ages, the poorest 'millennials' have less wealth than the

Acknowledgments. I am grateful for the valuable feedback that I received from Deirdre Bloome and Sasha Killewald, while writing this paper. This project has benefited from the generous support of the Social Sciences and Humanities Research Council of Canada (Grant #752-2017-0482) and the American Sociological Association (ASA Doctoral Dissertation Research Improvement Grant, 2025).

poorest 'baby boomers', *but* the richest 'millennials' actually have more wealth than their rich counterparts in the earlier cohort.

At the same time that wealth dynamics have been changing, there have also been dramatic shifts in the life-course dynamics of family patterns (see Bloome and Ang 2020; Sweeney 2002), educational attainment (see Bloome et al. 2018; Pfeffer 2018), and labor-market outcomes (see Cheng 2016; Song et al. 2020). However, many of these studies have focused on the cross-cohort changes to a person's individual-level characteristics, measured contemporaneously in adulthood. But a person's wealth levels, especially in early adulthood, are highly correlated with their parental and socioeconomic background that predates the transition to adulthood. In fact, the key engines of wealth accumulation—marriage, education, employment—are *also* shaped by a person's childhood experiences and initial socioeconomic position.

My study will bring together two segments of the literature, on the intergenerational basis for wealth inequality and changes to the historical patterns of wealth accumulation. Given what we know about the intergenerational persistence of the racialized wealth gap (see Killewald, Pfeffer, and Schachner 2017), any changes to the intergenerational basis for wealth attainment *could* have a marked impact on Black-White wealth inequality. In this study, I assemble a collection of 14 socioeconomic-background characteristics, in order to estimate (1) the cohort-specific role that these characteristics play in shaping wealth accumulation and wealth inequality, as well as (2) the cross-cohort role that these characteristics play in shaping wealth outcomes.

Using 33 years of longitudinal data from the Panel Study of Income Dynamics, I examine how the intergenerational basis for wealth accumulation has evolved over time, by comparing changes in asset levels across three cohorts of 35-year-olds, between 1988 and 2021. I use decomposition analyses to identify whether family origins are playing a larger or smaller role in explaining cohort changes in wealth and the racialized wealth gap. I find that shifts in the distribution of family origins have had an equalizing effect on cross-cohort inequalities between Black and White individuals. However, the racialized wealth gap has actually increased over time, because the equalizing effects of the changes in socioeconomic background were entirely offset by other factors. Moreover, within-cohort analyses reveal that intergenerational factors remain the largest contributor to the racialized wealth gap, regardless of time period or cohort change. Therefore, my study highlights the enduring significance of a person's socioeconomic background for explaining wealth inequality.

4.2 The Intergenerational Basis for Wealth Attainment

A person's wealth attainment is strongly associated with their socioeconomic-background characteristics (Charles and Hurst 2003; Killewald et al. 2017). As a socioeconomic resource, wealth is unique in that it can be maintained directly, through (1) inheritance and inter-household transfers and (2) heterogeneities in wealth returns and compounding growth over time. Historically, these two sources of direct wealth transmission have been salient for shaping wealth attainments in the United States. First, inheritance flows have become a larger share of national income, across many developed countries, which suggests that

private transfers of wealth are playing a larger role in shaping wealth attainments (Piketty 2011; Piketty and Zucman 2014). Second, people with higher initial values of wealth benefit from a quicker entry into capital markets with higher returns (Fagereng et al. 2020; Piketty and Zucman 2014), and they benefit from their reduced debt burden and concern with debt repayment (Dwyer, McCloud, and Hodson 2012; Houle and Addo 2019).

Yet, wealth is not the only background characteristic that shapes wealth attainments. Even after conditioning on parental wealth, Black children are still more likely than White children to experience downward wealth mobility and less likely to experience upward wealth mobility (Pfeffer and Killewald 2018). Therefore, to study the intergenerational basis for wealth accumulation, it is important to capture the full array of a person's socioeconomic background.

4.2.1 Historical Changes to Wealth

Across the population, the mean value of wealth has risen substantially since the 1980s. Studies have shown these increases are due to the appreciating value of assets at the top of the distribution (Piketty and Zucman 2014) and equity and housing revaluations (Kuhn, Schularick, and Steins 2020).

However, there have not been comparable increases at the middle or bottom of the wealth distribution. During the Great Recession, losses in wealth were greatest among families, around the median, whose home equity represented the largest part of their wealth portfolio (Pfeffer, Danziger, and Schoeni 2013). Additionally, recoveries were slower for these housing-heavy families in the years that followed the economic downturn (Pfeffer et al. 2013). By com-

parison, higher-wealth families with more-diversified portfolios experienced a quicker recovery, due to the higher rate of returns from investments and business assets (Killewald et al. 2017; Kuhn et al. 2020). Consequently, there has been rising inequality across the wealth distribution, driven by differences in the composition of wealth portfolios.

4.2.2 Racialized Wealth Inequality

Because Black families have historically been shut out from accumulating wealth (see Taylor 2019), White individuals are disproportionately represented at the top of the wealth distribution. Therefore, the rising inequality across the distribution of wealth also means that there is likely to be higher levels of racialized wealth inequality.

Black and Hispanic individuals are more likely to have zero or negative wealth (Bhutta et al. 2020), with one study finding that Black families with children have rates of net-worth poverty that are twice as large as White families with children (Gibson-Davis, Keister, and Gennetian 2021).

One of the major drivers of the racialized inequality in wealth is due to the large and persistent differences in homeownership rates (Killewald et al. 2017) However, even after conditioning on homeownership, Black and Hispanic families have historically accumulated less equity, due to differences in appreciation and concentrated disadvantage in neighborhoods (Krivo and Kaufman 2004). Studies of Black-White wealth inequality have shown that disparities in home equity are driven by lower valuations of homes (Perry, Rothwell, and Harsh-

barger 2018) and predatory lending and unequal foreclosures (Rugh and Massey 2010; Seamster and Charron-Chénier 2017).

Beyond homeownership, racialized wealth inequalities are driven by a number of different inequalities that fall along socioeconomic lines, such as lower levels of inheritance (Wolff and Gittleman 2014), higher debt burdens among young adults (Houle and Addo 2019), and the unequal rates of incarceration (Maroto 2015). Furthermore, the Great Recession widened racialized wealth inequalities, due to unequal losses and uneven recoveries (Pfeffer et al. 2013; Shapiro, Meschede, and Osoro 2013).

Ultimately, the racialized wealth gap cannot be attributed to differences in income, education, and demographic composition (Bhutta et al. 2020); therefore, preexisting historical inequalities play a central role (Shapiro et al. 2013). In this study, I examine how intergenerational inequalities have evolved to explain a larger (or smaller) share of the overall Black-White inequality in wealth.

4.3 Empirical Strategy

The objective of this paper is to investigate changes in the intergenerational basis for wealth accumulation and wealth inequality. Ultimately, my goal will be to decompose the total difference in wealth accumulation across cohorts, and between Black and White individuals, in order to examine whether wealth inequality is becoming increasingly tied to a person's socioeconomic background.

4.3.1 Identifying the Historical Changes to Wealth

To begin, I describe the mean levels of wealth across the entire population of 35-year-olds, as well as the population-wide distribution of wealth (i.e., the 10th, 25th, 50th, 75th, 90th percentiles). The decomposition framework that I implement requires a comparison of group-specific means; therefore, most empirical analyses are focused on identifying the cohort change and Black-White inequalities in the mean levels of wealth.

For my first key comparison—the cohort changes in wealth—I separately estimate the levels of wealth for 35-year-olds in three decades: (1) 1988–1999, or the '1990s'; (2) 2000–2009, or the '2000s'; (3) 2010–2021, or the '2010s'; and I also produce pooled estimates (4) across all three decades.

For my second key comparison—the racialized inequalities in wealth—I separately estimate the age-35 levels of wealth for: (1) non-Hispanic Black individuals; (2) non-Hispanic White individuals; and I also produce pooled estimates (3) across the total population, which includes the two groups of Black and White individuals, as well as all other racial/ethnic groups. I do not report the group-specific estimates for members of other racial/ethnic groups, due to limited sample size and within-group heterogeneity (e.g., combining Hispanic and Asian individuals). Even so, I decided not to drop these groups from the full analytic sample, because they represent a nontrivial share of the population—and one of my empirical goals is estimate population-wide changes to wealth across cohorts.[1]

[1]Although gender-based differences were not the focus of this paper, I also produced separate estimates for both men and women, respectively. In this paper, all findings are based on pooled samples of men and women.

Descriptively, I present the mean and distribution for three measures of wealth: (1) total net worth; (2) total assets; and (3) total debts. For the study's inferential analyses, I mostly focus on the interpretations of results from the asset-based analyses. (However, every analysis of total assets has a corresponding version, for total net worth, which can be found in Appendix B.) In many contexts, especially at the individual level, differences in net worth are crucial for shaping the lives of individuals and their families. However, for population-level analyses, I argue that assets are advantageous for between-group comparisons, because net worth can obscure the countervailing effects of assets and debts.

I selected total assets as my study's primary outcome for two main reasons. First, net worth—defined as the sum of all assets, subtracted by the sum of all debts—assumes a one-to-one conversion between asset value and debt value, such that a person with 10,000 dollars of asset holdings and 10,000 dollars of outstanding debt will be treated the same as a person with zero assets and no debts. But this assumption may not be warranted, given the range of different types of assets and debts. While an increase in asset value is almost always beneficial, there is a persuasive body of research that highlights the significant differences between "good debts," such as a home mortgage, and "bad debts," such as credit-card debt (Charron-Chénier and Seamster 2018). Consequently, the increase in a person's debt holdings is not always detrimental, depending on the debt's potential for acquiring new assets or increasing existing asset value. Yet, a net worth measure effectively assumes that a one-dollar increase in debt will completely diminish the potential benefits of a one-dollar increase in assets.

Second, a person's net worth combines two quantities that are frequently governed by different theoretical processes. For cohort comparisons, the timing of institutional changes that opened new channels for asset accumulation (Flores 2024; Tomaskovic-Devey and Lin 2011) might be decoupled from the timing of institutional changes that expanded the types and amount of debt holdings (Fligstein and Goldstein 2015; Krippner 2017). For population-level analyses, there may be significant variation between groups in terms of the share of people who accumulate assets and debts in tandem (i.e., a higher correlation) versus the share of people who accrue disproportionate levels of debt or assets (i.e., a lower correlation). Cross-cohort and between-group comparisons of total assets avoid the potential risk of countervailing trends between assets and debt that are baked into the measure of total net worth.

4.3.2 Estimating the Relationship Between Socioeconomic Background and Wealth

In order to evaluate the intergenerational basis for wealth inequality, I begin by describing how the intergenerational basis for wealth inequality is changing over time. I assembled a series of 14 measures of intergenerational, based on a person's parental socioeconomic status and childhood experiences, as well as five basic demographic characteristics. The demographic characteristics were included in every regression of the total population, and they were omitted from select group-specific regressions; for example, racial/ethnic identifiers were not unnecessary to include in Black- and White-specific regression models, but they were included in pooled regression models.

In addition to describing the cohort-specific means and proportions for each indicator of a person's socioeconomic background, I also calculate the changes in these measures across decade—for Black individuals, White individuals, and pooled across the total population.

Next, I calculate whether the intergenerational associations with age-35 wealth levels have increased (or decreased) over time. To do so, I compare the share of total variance in the outcome that is explained by the entire regression model, which I calculate by comparing the R-squared statistics of two regression models: (1) a full model, which includes all 14 indicators of a person's socioeconomic background, as well as the basic demographic characteristics; and (2) a basic model, which only includes the basic demographic characteristics. The difference between these two R-squared statistics represents the amount of variance in total assets (or total net worth) that can be explained by the entire set of background characteristics. A change in the difference between R-squared statistics denotes that a person's socioeconomic background has become a bigger (or smaller) 'determinant' of wealth over time.

Finally, I estimate two linear regressions of age-35 wealth levels. I begin by separately estimating the total associations between each measure of socioeconomic background and total assets (or total net worth), without any controls.[2] Then I jointly estimate the partial associations between the measures of socioeconomic background and each wealth outcome, controlling for the means of every other variable in the model (including basic demographic characteristics).

[2]I use the term "total association" to mean the zero-order correlation coefficient, between two variables, without the inclusion of any other measures included in the model.

$$\underbrace{Y^{35}_{igrd}}_{\substack{\text{Wealth levels}\\ \text{at age 35}}} = \alpha_{grd} + \underbrace{\sum_{j=1}^{14}\left(\beta^{j}_{grd} * \boldsymbol{S}^{j}_{igrd}\right)}_{\substack{\text{Socioeconomic}\\ \text{background}}} + \underbrace{\sum_{k=1}^{K}\left(\beta^{k}_{grd} * \boldsymbol{C}^{k}_{igrd}\right)}_{\substack{\text{Demographic}\\ \text{characteristics}}} + \epsilon_{grd} \tag{4.1}$$

Equation (4.1) outlines the full model for regressing each wealth outcome, Y^{35}_{igrd} (i.e., total assets or total net worth), on the entire collection of socioeconomic-background characteristics, $\boldsymbol{S}^{j}_{igrd}$, and basic demographic characteristics, $\boldsymbol{C}^{k}_{igrd}$, for every individual, i. Each beta (e.g., β^{j}_{grd}) represents the partial association between a specific measure, j, net of all other variables included in the model. Regressions were also run separately by gender, g, and racial/ethnic group, r, as well as the decade of age-35 wealth observations, d. (Each includes a pooled version.) Finally, the alpha (α_{grd}) and epsilon terms (ϵ_{grd}) represent the regression intercept and error term, respectively.

Ultimately, my objective is *not* to produce precise estimates of the specific association between each indicator of socioeconomic background and a person's levels of wealth (i.e., β^{j}_{grd}). The exercise is currently predictive, rather than inferential. The eventual objective is to estimate how much the cohort changes to wealth and Black-White wealth inequality can be explained by the *collective* set of intergenerational factors that shape wealth accumulation and wealth inequality (i.e., parental and childhood characteristics). The key reason for forgoing the individualized interpretation of specific associations is that between-group comparisons of regression coefficients are highly sensitive to the distribution of a predictor and the selection of reference values.

Taken together, my study's key predictor of interest is the difference in *means* for the entire series of socioeconomic-background characteristics. Next, I discuss how I will implement a statistical decomposition to estimate how much the changes in the distribution to socioeconomic background have contributed to cohort changes in wealth and Black-White wealth inequalities.

4.3.3 Identifying How Family Origins Shape Wealth Accumulation

I use a flexible decomposition approach to compare the total changes in wealth across cohorts, in order to estimate the extent to which intergenerational factors have driven the historical changes in wealth accumulation, among 35-year-olds, across three decades.

All inputs for the decomposition come from Equation (4.1)—the group-specific mean values on socioeconomic-background characteristics, $\boldsymbol{S}^{j}_{igrd}$, and basic demographic characteristics, $\boldsymbol{C}^{k}_{igrd}$, and the group-specific associations with each set of characteristics (i.e., β^{k}_{grd} and β^{k}_{grd}, respectively).

I outline my decomposition approach in Equation (4.2), where I compare cohort change across two decades, where $D1$ represents the most-recent decade and $D0$ represents the earlier decade being compared. In the manuscript, I focus on the comparison over the three decades (2010s – 1990s), but the same decomposition approach could be used to compare any combination of cohorts (i.e., 2000s – 1990s; 2010s – 2000s). Although I focus on the three-decade comparison in the manuscript, the results for all three cohort comparisons are included in Appendix B.

$$
\begin{aligned}
\underbrace{\left(Y^{35}_{igr\boldsymbol{D1}} - Y^{35}_{igr\boldsymbol{D0}}\right)}_{\substack{\text{Cohort change in}\\ \text{age-35 wealth levels,}\\ \text{comparing decades}\\ \boldsymbol{D1}\ -\ \boldsymbol{D0}}} \quad = \quad & \underbrace{\sum_{j=1}^{14}\left(\boldsymbol{S}^{j}_{igr\boldsymbol{D1}} - \boldsymbol{S}^{j}_{igr\boldsymbol{D0}}\right) * \beta^{j}_{gr\boldsymbol{D0}}}_{\substack{\textbf{A1}\text{: Difference in the means}\\ \text{of socioeconomic background}}} \\
& + \quad \underbrace{\sum_{j=1}^{14}\left(\beta^{j}_{gr\boldsymbol{D1}} - \beta^{j}_{gr\boldsymbol{D0}}\right) * \boldsymbol{S}^{j}_{igr\boldsymbol{D1}}}_{\substack{\textbf{A2}\text{: Difference in the wealth associations}\\ \text{with socioeconomic background}}} \\
& + \quad \underbrace{\sum_{j=1}^{K}\left(\boldsymbol{C}^{k}_{igr\boldsymbol{D1}} - \boldsymbol{C}^{k}_{igr\boldsymbol{D0}}\right) * \beta^{k}_{gr\boldsymbol{D0}}}_{\substack{\textbf{B1}\text{: Difference in the means}\\ \text{of basic demographic characteristics}}} \\
& + \quad \underbrace{\sum_{k=1}^{K}\left(\beta^{k}_{gr\boldsymbol{D1}} - \beta^{k}_{gr\boldsymbol{D0}}\right) * \boldsymbol{C}^{k}_{igr\boldsymbol{D1}}}_{\substack{\textbf{B2}\text{: Difference in the wealth associations}\\ \text{with basic demographic characteristics}}} \\
& + \quad \underbrace{\left(\alpha_{gr\boldsymbol{D1}} - \alpha_{gr\boldsymbol{D0}}\right)}_{\substack{\textbf{C}\text{: Difference in the}\\ \text{regression intercepts}}}
\end{aligned}
\tag{4.2}
$$

Although the decomposition framework that I implemented can produce estimates of five different components, my main empirical goal is to isolate the influence of the changing distribution of socioeconomic-background characteristics (due to the issues with differentiating specific associations from the regression intercept).

Based on the decomposition outlined in Equation (4.2), I display three decomposed quantities in the results of my analyses. First, I draw inferences about my key predictor of interest—the changes in how socioeconomic characteristics are distributed across the population (component A1). I am also able to isolate

the change in the distribution of means of basic demographic characteristics (component B1). Finally, the remaining components can be grouped together, representing every regression term, including all associations and the intercept (components A2+B2+C).

4.3.4 Estimating the Intergenerational Basis for Wealth Inequality

Next, I decompose the total difference in Black-White wealth inequality, in order to evaluate the intergenerational basis for the racialized wealth gap. There is one key comparison, calculating the difference in age-35 wealth levels for Black and White individuals—within a particular decade or pooled across all cohorts.

I recycle the same exact decomposition approach that I outlined in Equation (4.2), except that instead of the subscripts for the comparison of decades (i.e., $_{D1-D0}$), I substitute the Black and White subscripts (i.e., $_{B-W}$). Finally, I replace the remaining subscripts, $_{igr}$, with their decade-specific counterpart, $_{igd}$. Everything else operates the same. Although the equation estimates five components, I display three decomposed quantities that explain the total difference in Black-White wealth inequality (i.e., components A1, B1, and A2+B2+C).

After generating decade-specific estimates of how family origins contribute to racialized wealth inequality, the follow-up objective is to evaluate how much of the racialized inequality in wealth is due to differences in socioeconomic background. To answer this question, I modify my decomposition framework to allow for a double decomposition—estimating *changes* in the *differences* between the age-35 wealth levels of Black and White individuals.

In Equation (4.3), I implement this double decomposition. To begin, the key comparison is the cohort change, $_{D1-D0}$, in Black-White differences—denoted by the following subscripts, $_{(B-W_{D1})-(B-W_{D0})}$. For the sake of brevity, Black-White comparisons have been collapsed into a single term. For example, the Black-White difference in socioeconomic background, during the 1990s, $_{D1}$, has been modified from its original two terms $\left(S^{j}_{igB_{D1}} - S^{j}_{igW_{D1}}\right)$, and shortened into one single term $\left[S^{j}_{igB-W_{D1}}\right]$.

$$
\begin{aligned}
\underbrace{\left(Y^{35}_{igB-W_{D1}} - Y^{35}_{igB-W_{D0}}\right)}_{\substack{\textbf{Double Decomposition:}\\ \text{Cohort change in the total difference in Black–White wealth inequality, comparing decades } (B-W_{D1}) \text{ – } (B-W_{D0})}} &= \underbrace{\sum_{j=1}^{14}\left(\left[S^{j}_{igB-W_{D1}}\right] * \beta^{j}_{grW_{D1}}\right) - \left(\left[S^{j}_{igB-W_{D0}}\right] * \beta^{j}_{grW_{D0}}\right)}_{\substack{\textbf{A1: Cohort change in the difference in the means}\\ \text{of socioeconomic background}}} \\
&+ \underbrace{\sum_{j=1}^{14}\left(\left[\beta^{j}_{gB-W_{D1}}\right] * S^{j}_{igB_{D1}}\right) - \left(\left[\beta^{j}_{gB-W_{D0}}\right] * S^{j}_{igB_{D0}}\right)}_{\substack{\textbf{A2: Cohort change in the difference in the wealth}\\ \text{associations with socioeconomic background}}} \\
&+ \underbrace{\sum_{j=1}^{K}\left(\left[C^{k}_{igB-W_{D1}}\right] * \beta^{k}_{gW_{D1}}\right) - \left(\left[C^{k}_{igB-W_{D0}}\right] * \beta^{k}_{gW_{D0}}\right)}_{\substack{\textbf{B1: Cohort change in the difference in the}\\ \text{means of basic demographic characteristics}}} \\
&+ \underbrace{\sum_{k=1}^{K}\left(\left[\beta^{k}_{gB-W_{D1}}\right] * C^{k}_{igB_{D1}}\right) - \left(\left[\beta^{k}_{gB-W_{D0}}\right] * C^{k}_{igB_{D0}}\right)}_{\substack{\textbf{B2: Cohort change in the difference in the wealth}\\ \text{associations with basic demographic characteristics}}} \\
&+ \underbrace{\left(\alpha_{gB-W_{D1}} - \alpha_{gB-W_{D0}}\right)}_{\substack{\textbf{C: Cohort change in the difference}\\ \text{in the regression intercepts}}}
\end{aligned}
\tag{4.3}
$$

Each component now represents the *cohort change* in the original difference being compared. Just as with the previous decomposition approaches, I present

results of three main sets of components. My target quantity, in Equation (4.3), is now the cohort change in the Black-White differences in how socioeconomic background is distributed across the population (component A1). I can continue to isolate the cohort change in the Black-White differences in the distribution of basic demographic characteristics (component B1). Finally, all terms from the regression equation are grouped together, representing the cohort change in the Black-White differences in associations and the intercept (components A2+B2+C).

Overall, my study's empirical analyses allow me to examine 30 years of change in how parental characteristics and childhood experiences are distributed—and the extent to which socioeconomic background shapes wealth dynamics in adulthood. But, instead of focusing on the estimation of specific associations, I have adopted an empirical design that permits me to investigate how the intergenerational basis for wealth accumulation and wealth inequality have changed over time.

4.4 Data and Sample

The ideal data for estimating the Black-White differences in the intergenerational persistence of poverty require both (*i*) repeated measures of income and (*ii*) families being observed for at least two generations. I use the Panel Study of Income Dynamics (PSID), because of its unique features as the world's longest-running longitudinal household survey, which began in 1968 with a nationally representative panel of more than 5,000 families in the United States.

The specific data file that I used to construct my sample comes from the PSID's Social, Health, and Economic Longitudinal File (PSID-SHELF), due to its harmonized socioeconomic measures and multigenerational data structure (Daumler et al. 2025).

Leveraging three decades of the PSID, I have generated a large cohort-based sample of Americans, who have an observed value of wealth at the age of 35, between the years of 1988 and 2021.

My initial sampling frame consisted of 11,643 individuals, who were observed at the age of 35 (or two other proximate ages), between the years of 1988 and 2021. Individuals were further required to be the current reference person or spouse/partner of a PSID family unit, during their age-35 observation, and they were required to have a nonmissing value of racial/ethnic identity.

Overall, 6,259 members of the sampling frame satisfied the inclusion criteria for my analytic sample. First, I dropped 192 individuals who had zero or missing values on the PSID's longitudinal family weights. Second, I dropped 5,192 individuals who had no survey observations as children.

See Table 4.1, for an overview of the sample. The analytic sample features a diverse array of 35-year-old Americans, spanning three decades: 1988–1999 (N = 2,442); 2000–2009 (N = 1,363); and 2010–2021 (N = 2,454). Additionally, my analytic sample includes a large number of non-Hispanic Black individuals (N = 2,512) and non-Hispanic White individuals (N = 3,425).

Next, I construct a comprehensive set of wealth measures, based on each person's total net worth, total assets, and total debts. To be included in the sample, an individual was required to have wealth measures available at the

age of 35. If a person's 35th birthday occurred in a non-survey year or when the wealth questionnaire was not collected,[3,4] then I used their most-proximate observation of wealth, at either ages 36 or 37.[5] To reduce the potential effects of wealth's skewed distribution, I top-code values at the 99th percentile,[6] by assigning the average value of everyone in the top 1 percent of the distribution—in order to preserve the overall mean of each wealth measure. Finally, I adjust for inflation, using the Personal Consumption Expenditures Price Index, and all values of wealth (and income) are expressed in 2024 dollars.

In addition to age-35 wealth levels, I create a series of 14 socioeconomic-background characteristics that were measured in adolescence (i.e., at age 15, if available, or the oldest observation between the ages of 8 and 14). This collection of parental and childhood characteristics includes: (1) grew up in the South (ref. did not live in the South); (2) low birth weight (ref. not low birth weight); (3) parents were married, adolescence (ref. was not married); (4) lived with two birth parents, adolescence (ref. did not live with); (5) mother employed, adolescence (ref. was not working); (6) father employed, adolescence (ref. was not working); (7) parents owned their home, adolescence (ref. did not own home); (8) parents in poverty, adolescence (ref. were not in

[3]Respondents were interviewed annually until 1997, when it switched to biennial survey years. Since then, half of the PSID sample will have their 35th birthday in a non-survey year.

[4]The PSID did not start collecting wealth measures until 1984. Initially, the wealth questionnaire was collected every five years (1984, 1989, 1994, 1999). From 1999 until present, the wealth questionnaire has been collected every two years (because the PSID switched to biennial survey interviews in 1997). Therefore, for the first 15 years, a significant share of the sample were missing a wealth observation at exact-age 35.

[5]Roughly two-thirds of my analytic sample had their wealth observations collected at age 35 (N = 4,069); one-third had their wealth measured at age 36 (N = 2,066); and only 2 percent of the sample had a wealth observation at age 37 (N = 124).

[6]Net worth measures were also bottom-coded at the 1st percentile.

poverty); (9) parental family income (mean-centered); (10) mother's years of education (mean-centered); (11) father's years of education (mean-centered); (12) mother's age at birth (mean-centered); (13) father's age at birth (mean-centered); and (14) number of siblings (mean-centered).[7]

I also included a small number of basic demographic characteristics: (15) female (ref. male); (16) Black, non-Hispanic (ref. not Black); (17) other racial/ethnic group (ref. not other); (18) birth year (mean-centered); and (19) age-35 observation in 2000s (ref. not 2000s); and (20) age-35 observation in 2010s (ref. not 2010s).

For each mean-centered variable, four sets of covariates were created: three cohort-specific variables, for each decade (1990s, 2000s, 2010s); and a cross-cohort variable, pooled across all three decades. I imputed any missing values of adolescent background characteristics, though item nonresponse was minimal, because members of the sample were required to have at least one childhood observation. All of my empirical analyses are estimated separately by gender, racial/ethnic group, and decade of age-35 observation—and I also generate pooled estimates for each category (i.e., analyses of both men and women, all racial/ethnic groups, and all three cohorts).

[7] Note that parental wealth was not included as a covariate, because the PSID did not collect wealth measures prior to 1984, when socioeconomic-background characteristics were collected (when sample members were adolescents). However, the inclusion of parental income should capture much of the variation in parental economic characters, given the moderate correlation between income and wealth (Killewald et al. 2017:389–391).

4.5 Historical Changes to the Wealth Distribution

Across the entire population of 35-year-olds, inequalities in the mean values of wealth appear to have increased, with a widening gap between the top and bottom of the wealth distribution. As Figure 4.1 reveals, the median values of total net worth and total assets have decreased, between the 1990s and the 2010s.

By contrast, the mean value of total net worth has remained relatively stable, while the mean value of total assets has increased over time. The 90th percentile distribution in assets increased substantially in the 2010s, relative to the 1990s.

During the same 30-year period, there have been a concurrent set of changes in the distribution of socioeconomic-background characteristics. Table 4.1 shows the mean values of each socioeconomic background indicator for Black and White individuals, across each decade (and pooled across all three decades). Values in parental family characteristics (i.e., married, lived with two birth parents, number of siblings) all decreased from the 1990s to the 2000s. On the other hand, values of parental education characteristics (i.e., mother's and father's years of education) increased from the 1990s to the 2000s.

Perhaps counterintuitively, mother's and father's age at birth decreased from the 1990s to the 2010s, but I suspect that this could be partially explained by (a) the higher number of siblings meaning that parents were more likely to have children at older ages; and (b) potential differences in the timing of wealth observations for the 1990s cohort, given that the wealth questionnaire was only collected every five years (as opposed to every two years, beginning in 1999).

At the aggregate, wealth inequalities between Black and White Americans have remained extremely large. In Figure 4.2, the distributions of wealth are presented for Black and White individuals, across the 1990s, 2000s, and 2010s. Looking at the shapes of the distribution—at every distributional threshold, White families have values of net worth and assets that are between 5 and 10 times larger than their Black counterparts.

On the other hand, the mean values of wealth, for Black and White individuals, are comparatively closer together. In the 2010s, Black families had an average of 81,000 dollars in assets, 48,000 dollars in debt, and, therefore, 34,000 dollars in total net worth. By comparison, White families had an average of 396,000 dollars in assets, 175,000 dollars in debt, and, therefore, 215,000 in total net worth.

The primary objective, for this study, is to explain how much of the changes in wealth are due to the shifts in the distribution of family origins—background characteristics that precede any family, educational, and labor-market outcomes in adulthood.

4.6 The Influence of Family Origins on Cohort Changes in Wealth

I begin by describing cross-cohort changes to the intergenerational basis for (1) changes in the wealth accumulation and (2) racial/ethnic inequalities in wealth, based on a collection of 14 socioeconomic-background characteristics.

In Figure 4.3, I estimate how much variance in wealth can be explained by socioeconomic background. Aside from the large change in the 2000s (for Black

individuals), overall, a person's socioeconomic background explains between 5 and 10 percent of the variance in total assets (and between 3 and 7 percent of the variance in total net worth). In the 2000s, family background characteristics explained more than 20 percent of the variance in wealth attainment for Black individuals, which could perhaps be driven by the outsize effect of the Great Recession on Black homeowners (Pfeffer et al. 2013).

Overall, there is a modest trend downward in the share of variance in each wealth outcome that is attributable to the distribution of socioeconomic-background characteristics. This could be an indicator of changes to the intergenerational basis for wealth attainment; however, a formal decomposition will be required to make any inferences about how socioeconomic-background characteristics are influencing cross-cohort changes in wealth accumulation and wealth inequality.

Over the last three decades, total assets have increased, at the mean, for both Black and White individuals. As Table 4.2 shows, asset value has increased by 77,000 dollars, from the 1990s to the 2010s—as evidenced by the total difference in means assets across cohorts. However, the increase in total assets has been higher for White individuals than Black individuals. At the mean, assets for White people have increased from 306,000 dollars to 396,000 dollars. For Black individuals, these same values of assets have increased from 67,000 dollars to 81,000 dollars (see Table 4.1, for the group-specific mean values). Notably, the absolute change in total assets is a function of the difference in starting points. However, even in relative terms, the gap in total assets increased,

with White individuals experiencing a 25 percent growth in total assets, and Black individuals experiencing a 19 percent growth in total assets.

Changes in the distribution of socioeconomic-background characteristics had a differential effect on the cohort change in total assets, when comparing Black and White individuals. Component A1, in Table 4.2, reveals the share of the total change in mean assets across decades that can be attributed to each group's change in the distribution of socioeconomic-background characteristics. For Black individuals, the cohort change in their socioeconomic-background characteristics led to an increase of 86,000 dollars in the 2010s, compared to the 1990s. Changes in socioeconomic background, at the mean, had large positive effects on the asset growth for Black individuals (177,000 dollars) and large negative effects on the asset growth for White individuals (-44,000 dollars), between the 2010s and the 1990s. By comparison, changes in the demographic composition of each racial/ethnic group—namely, gender and age distribution—had only a very small effect, producing a decrease of 3,700 dollars in total assets for White individuals and a decrease of 3,450 dollars for Black individuals. However, other factors partially offset the increase in total assets for Black individuals, reducing the would-be growth from 177,000 dollars to the actual growth of 14,000 dollars. On the other hand, for White individuals, all other factors, beyond the distribution of family characteristics, helped to offset their losses entirely; therefore, White individuals still experienced a rising level of total assets (90,000 dollars), despite the losses associated socioeconomic-background characteristics (-44,000 dollars).

Of course, it should be underscored that we are examining mean values of total assets, which are bound to be affected by the tail end of the wealth distributions. There is an open question about how much the changes in mean assets can be explained by changes to the entire distribution of wealth, which would be observed at either the 10th, 25th, or 50th percentiles, or if these changes are entirely driven by the upper end of the distribution, due to rising asset value at the 75th and 90th percentiles.

An examination of the cohort changes in total net worth, Appendix Table B.2, shows a different story. After bringing total debts into the mix, the mean value of total net worth decreased by 5,500 dollars for Black individuals, between the 2010s and 1990s, though it remained relatively stable for White individuals (-100 dollars). Similar to assets, changes to socioeconomic background were associated with an 80,000-dollar increase in net worth for Black individuals and a 33,000-dollar decrease in net worth for White individuals.

But the question is what do these cohort changes in Black and White wealth mean for overall racialized inequalities in wealth? To answer this question, I move from a group-specific decomposition across cohorts, to a Black-White decomposition within each cohort.

4.7 Intergenerational Changes to Racialized Wealth Inequalities

Overall, the inequality between Black and White individuals reached its highest point in the 2010s. In Table 4.3, we can see that the Black-White gap in total assets ranged from a low of -159,000 dollars, in the 2000s, to a high of -315,000

dollars, in the 2010s (and the racial wealth gap was -239,000 dollars in the 1990s).

Notably, inequality in socioeconomic background consistently been the primary contributor to Black-White wealth inequality. Regardless of the decade being examined, differences in the distribution of socioeconomic background have always contributed at least 160,000 dollars toward the overall racial/ethnic inequality in total assets. The contributions of socioeconomic background were actually larger in the 1990s and 2000s, compared to the 2010s—dropping from around -291,000 to -168,000 dollars.

Moreover, all other factors (aside from socioeconomic background) began to exacerbate the Black-White wealth gap in the 2010s—as opposed to the offsetting effect that these other factors had on the losses that could be attributed to family origins. In other words, the contributions of other factors were contributing an additional 147,000 dollars to racial/ethnic wealth inequalities in the 2010s.

Finally, in order to evaluate how much changes to family origins have contributed to Black-White wealth inequality, I produce a double decomposition of cohort change in the overall Black-White difference in total assets. Table 4.4 shows that the inequalities in total assets between Black and White individuals has grown larger over time, with a 75,000-dollar increase in the racial wealth gap, comparing the 2010s to the 1990s.

However, over the last 30 years, the distribution of socioeconomic background actually had an offsetting effect on the growth in racialized inequality. All things equal, cohort changes in the inequality in socioeconomic-background

characteristics would have closed the gap by 123,000 dollars. However, other factors, aside from the distribution of socioeconomic-background characteristics, had a disequalizing effect on the gap in total assets that was nearly 1.5 times larger than the cohort change attributed to the distribution of socioeconomic-background characteristics.

The key take-away from these findings is that changes in socioeconomic-background characteristics have actually reduced Black-White wealth inequality, but this contribution has been completely offset and eclipsed by other factors. As a result, the Black-White wealth inequalities have grown larger, despite changes to socioeconomic-background characteristics. Even though changes to socioeconomic-background characteristics have had an equalizing effect across cohorts, the within-cohort analysis show that differences in socioeconomic background remain the primary driver of racialized wealth inequalities. In fact, prior to the 2010s, differences in socioeconomic-background characteristics were the sole basis for these wealth inequalities, and at the same time that socioeconomic-background characteristics became less of a contributor to the wealth gap, changes in other factors began to have a disequalizing effect on the wealth gap. In other words, inequalities in socioeconomic background have always been disequalizing, across all three cohorts and timeframes—but they have become slightly less disequalizing in the 2010s. Despite this fact, the intergenerational factors remain the dominant mechanism for explaining changes to wealth accumulation and wealth inequality.

4.8 Discussion

This study investigates the intergenerational basis for wealth inequality, by estimating three key estimates: (1) cross-cohort changes in wealth accumulation; (2) cohort-specific Black-White wealth inequalities; and (3) the total cohort change in Black-White wealth inequalities. By comparing the associations between a person's socioeconomic background and their level of total assets, across three cohorts of 35-year-old Americans, my findings shed light on the shifting intergenerational basis for contemporary wealth inequality. The empirical results of my study reveal three main findings.

First, I find that racialized inequalities in family origins are narrowing for Black individuals, compared to their White peers. As a result, intergenerational inequalities are responsible for reducing the growth in total assets for White individuals, at age 35, and increased growth in total assets for Black individuals.

Second, I show that the racialized wealth gap has actually increased, between the 1990s and 2010s, but these increases are not explained by intergenerational factors. By contrast, my results show that cohort change in socioeconomic background is actually responsible for a reduction in the overall Black-White wealth inequality. However, the equalizing effects of the changes to socioeconomic background were entirely offset by other factors.

Third, although there have been some changes to the distribution of socioeconomic-background characteristics, I show that intergenerational inequalities remain the largest contributor to the racialized wealth gap, within any given cohort, regardless of any cohort change that has occurred. In other

words, the narrowing of intergenerational inequality is modest, compared to the total size of the initial inequality in socioeconomic background.

In this study, I focus on examining the difference in mean wealth, but the literature shows that much of the story about historical changes to wealth lies at the bottom, median, and top of the distribution (Gruijters et al. 2023). Therefore, there is an analytic opportunity to estimating the role of socioeconomic background on wealth at different parts of the distribution. The potential limitations from using the non-linear regression models required for such a distributional analysis is that decomposition of the predictors becomes more difficult when the goal is to compare the distributions and associations of specific measures.

This study provides the foundation for a number of promising opportunities for future research, based on the analysis of cohort change. First, as discussed, a direction for future research is the turn toward examining the distribution of wealth more directly, including different quantiles (e.g., 10th, 50th, 90th percentiles), as well as interquantile differences (e.g., the 10th–50th percentiles or the 10th–90th percentiles). Second, I focus on examining the values of total assets and total net worth at age 35, but there are many questions about the role of age and timing of wealth accumulation. One such approach would be to separate how family background separately associates with wealth starting points (e.g., at age 25) versus levels of accumulation (e.g., between ages 25 and 35). The comparison of starting points and accumulation can also extend itself nicely to a larger study of age-based trajectories across adulthood. Third, while I focus on examining the role of family background, by estimating associations with age-35 wealth, the intergenerational basis for wealth accumulation and wealth inequality

may operate through intermediate demographic and socioeconomic outcomes. A future direction for research, therefore, could estimate the indirect effects of socioeconomic background on wealth, through the conditional probabilities of marriage, educational attainment, or other labor-market outcomes. Fourth, there are considerable analytic and theoretical opportunities to document the structural drivers of intergenerational wealth inequality. Since the 1980s, the United States has borne witness to large-scale changes to political, historical, and spatial conditions that govern how people accumulate wealth—and the extent to which a person's socioeconomic background shapes their wealth attainment.

Ultimately, my research affirms the large role that family origins plays in shaping wealth accumulation and wealth inequality. Although there has been cohort change in the extent to which family background shapes the wealth attainment of Black and White individuals, there is one fact that remains unchanged. In the United States, over the last 30 years, intergenerational inequality remains the largest determinant of the racialized wealth gap.

4.9 Tables and Figures

All of the tables and figures for Chapter 4 are included on the pages that follow, in the order that they were mentioned in the text.

Table 4.1: Sample Characteristics, for Two Age-35 Cohorts, by Racial/Ethnic Group

	Total population		Black individuals		White individuals	
	1990s	2010s	1990s	2010s	1990s	2010s
Total net worth, age 35 (dollars)						
Mean	180,169	188,694	38,958	33,449	215,337	215,226
Standard deviation	536,772	654,109	98,278	153,205	598,408	646,493
10th percentile	-863	-32,233	-1,907	-31,476	0	-34,331
25th percentile	9,532	0	0	0	20,517	835
50th percentile	58,837	31,616	8,296	3,413	80,179	49,880
75th percentile	168,239	150,661	38,518	49,397	194,480	209,980
90th percentile	400,997	415,442	115,593	111,778	451,821	516,599
Total assets, age 35 (dollars)						
Mean	259,953	336,905	67,059	81,347	306,232	395,856
Standard deviation	551,772	772,778	129,161	199,194	606,525	794,631
10th percentile	2,617	1,242	0	0	8,233	3,579
25th percentile	24,194	12,438	893	971	49,650	21,919
50th percentile	133,713	112,471	16,450	12,692	172,511	193,400
75th percentile	303,710	364,304	97,978	75,760	346,129	439,703
90th percentile	559,872	760,706	187,567	276,053	620,905	885,257
Total debts, age 35 (dollars)						
Mean	83,823	144,960	28,101	47,812	96,127	174,768
Standard deviation	108,824	222,873	59,780	100,250	110,642	244,346
10th percentile	0	0	0	0	0	0
25th percentile	3,417	494	0	0	8,627	7,158
50th percentile	44,765	53,228	2,136	1,650	62,426	98,998
75th percentile	127,059	215,318	20,706	35,792	143,418	242,663
90th percentile	221,955	367,460	104,650	177,212	236,970	403,609
Socioeconomic background						
Grew up in the South	0.27	0.32	0.59	0.56	0.21	0.25
Low birth weight	0.06	0.06	0.07	0.09	0.06	0.05
Parents were married, adolescence	0.83	0.72	0.57	0.37	0.88	0.81
Two birth parents, adolescence	0.78	0.63	0.45	0.26	0.85	0.72
Mother employed, adolescence	0.78	0.71	0.43	0.62	0.84	0.76
Father employed, adolescence	0.93	0.91	0.83	0.89	0.95	0.92
Parents owned their home, adolescence	0.79	0.72	0.49	0.43	0.85	0.82
Parents in poverty, adolescence	0.17	0.23	0.54	0.49	0.09	0.13
Parents' family income, adolescence (dollars)	430,242	114,303	46,327	56,912	435,959	134,451
Mother's years of education	12.2	13.6	10.7	13.1	12.5	14.1
Father's years of education	12.1	13.6	9.3	12.3	12.7	14.1
Mother's age at birth	27.4	26.4	27.7	24.1	27.4	27.1
Father's age at birth	30.8	29.4	33.9	29.0	30.1	29.6
Number of siblings	3.2	1.9	4.3	2.3	2.9	1.8
Demographic characteristics						
Female	0.54	0.51	0.66	0.49	0.51	0.51
White, non-Hispanic	0.77	0.70	0.00	0.00	1.00	1.00
Black, non-Hispanic	0.17	0.19	1.00	1.00	0.00	0.00
Other racial/ethnic group	0.05	0.11	0.00	0.00	0.00	0.00
Birth year	1958.3	1981.0	1958.4	1981.3	1958.3	1980.6
Unweighted *N*	2,442	2,454	1,024	997	1,329	1,281

Note: Aggregated sample characteristics across all cohorts are available in Appendix Table B.1. [Back to text.]

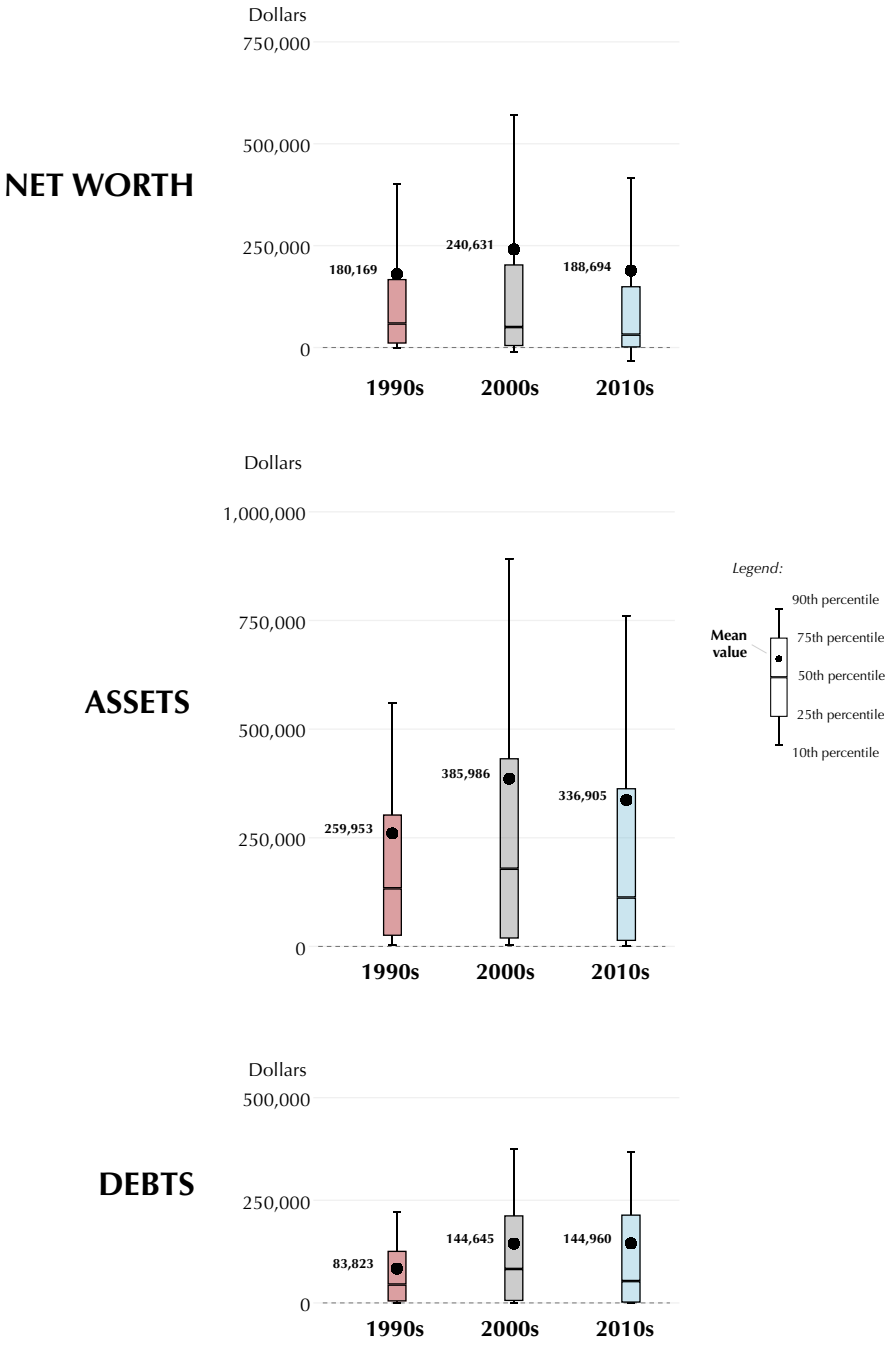


Figure 4.1: Historical Changes to Wealth at Age 35

The weighted distributions of total net worth, total assets, and total debts—each measured at age 35. The black circle represents the mean value, and the horizontal line (and corresponding numerical value) represent the median value. All estimates are weighted to be representative of U.S. men and women, at age 35, between 1988 and 2021. N = 6,259 individuals. [Back to text.]

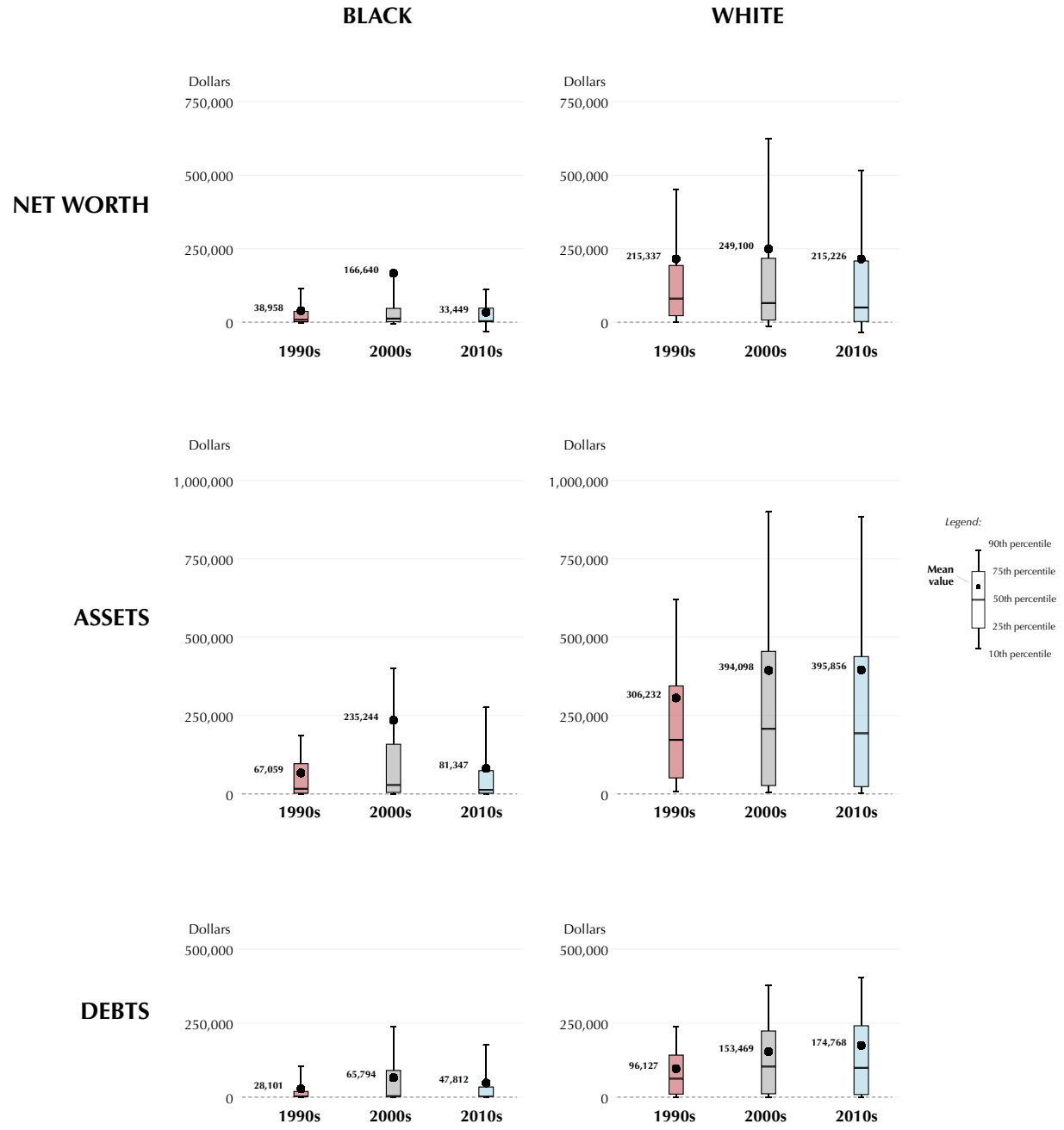


Figure 4.2: Comparison of Historical Changes to Wealth at Age 35, by Racial/Ethnic Group

The weighted distributions of total net worth, total assets, and total debts—each measured at age 35. The black circle represents the mean value, and the horizontal line (and corresponding numerical value) represent the median value. All estimates are weighted to be representative of U.S. men and women, at age 35, between 1988 and 2021. N = 2,512 Black individuals; N = 3,425 White individuals. [Back to text.]

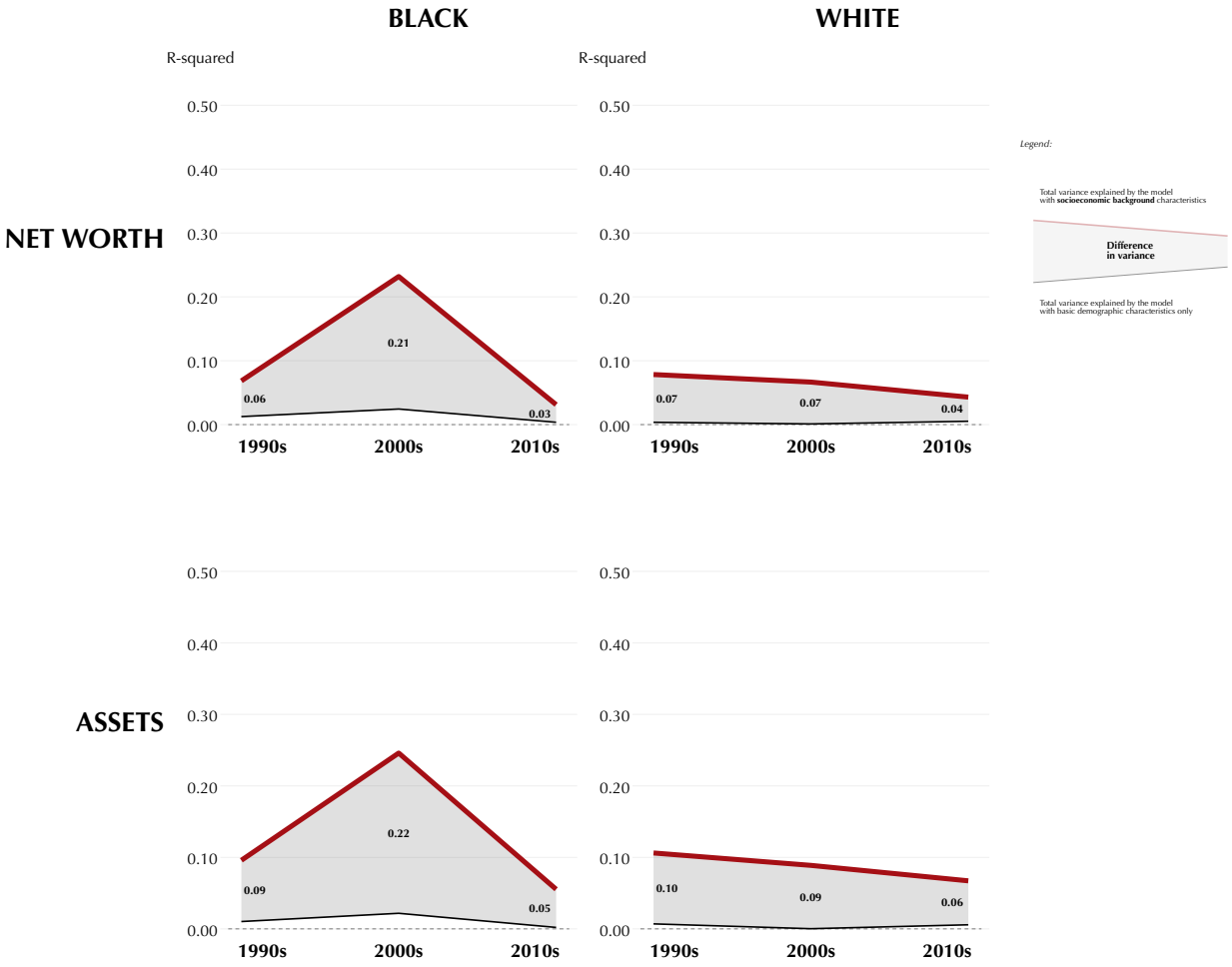


Figure 4.3: Total Variance in Two Wealth Outcomes, Explained by Socioeconomic Background Characteristics, for Each Age-35 Cohort, and by Racial/Ethnic Group

This figure displays two sets of R-squared statistics, measuring the total amount of variance in total net worth and total assets, measured at age 35, that can be explained by the full model (bold red curve) and the basic model (thin black curve). The shaded regions (and the corresponding numerical values) represent the difference in variance that can be uniquely explained by the addition of socioeconomic background characteristics to the full model. All estimates are weighted to be representative of U.S. men and women, at age 35, between 1988 and 2021. N = 6,259 individuals. [Back to text.]

Table 4.2: Decomposition of the Cohort Change in Total Assets, for Each Racial/Ethnic Group

	Decomposition of the cross-cohort difference in mean assets	
	2010s – 1990s	
	Dollars	Percent
PANEL 1: Total population of men and women		
Explained by socioeconomic background:		
Cohort change in socioeconomic background, means (Component A1)	-20,568	-26.7
Unexplained by socioeconomic background:		
Cohort change in demographic composition, means (Component B1)	-8,969	-11.7
Cohort change in all regression coefficients (Components A2+B2+C)	106,488	138.4
Total cohort change in mean assets	76,952	100.0
PANEL 2: Black men and women		
Explained by socioeconomic background:		
Cohort change in socioeconomic background, means (Component A1)	177,324	>1000
Unexplained by socioeconomic background:		
Cohort change in demographic composition, means (Component B1)	3,450	24.1
Cohort change in all regression coefficients (Components A2+B2+C)	-166,486	<-1000
Total cohort change in mean assets	14,288	100.0
PANEL 3: White men and women		
Explained by socioeconomic background:		
Cohort change in socioeconomic background, means (Component A1)	-44,315	-49.4
Unexplained by socioeconomic background:		
Cohort change in demographic composition, means (Component B1)	-3,703	-4.1
Cohort change in all regression coefficients (Components A2+B2+C)	137,643	153.6
Total cohort change in mean assets	89,624	100.0

Note: The full set of cohort comparisons for the asset-based analyses are available in Appendix Table B.2, and the decomposition of the cohort change in *total net worth* is available in Appendix Table B.3. [Back to text.]

Table 4.3: Decomposition of the Black-White Difference in Total Assets, Across Cohorts

	Decomposition of the racial/ethnic difference in mean assets	
	Black – White	
	Dollars	Percent
PANEL 1: Black and White individuals, 1990s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-291,104	121.7
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	4,104	-1.7
Difference in all regression coefficients (Components A2+B2+C)	47,827	-20.0
Total difference in mean assets by racial/ethnic group	-239,173	100.0
PANEL 2: Black and White individuals, 2000s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-262,484	165.2
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	-1,112	0.7
Difference in all regression coefficients (Components A2+B2+C)	104,742	-65.9
Total difference in mean assets by racial/ethnic group	-158,854	100.0
PANEL 3: Black and White individuals, 2010s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-168,128	53.5
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	5,327	-1.7
Difference in all regression coefficients (Components A2+B2+C)	-151,708	48.2
Total difference in mean assets by racial/ethnic group	-314,509	100.0

Note: The decomposition of the Black-White difference in *total net worth* is available in Appendix Table B.4. [Back to text.]

Table 4.4: Decomposition of Cohort Change in the Black–White Difference in Total Assets, Across Cohorts

	Decomposition of the cohort change in the racial/ethnic difference in mean assets	
	$(B-W)_{2010s} - (B-W)_{1990s}$	
	Dollars	Percent
Black and White individuals, cohort change: 2010s – 1990s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	122,976	-163.2
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	1,223	-1.6
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	-199,535	264.9
Total cohort change in the total difference in mean assets by racial/ethnic group	-75,336	100.0

Note: The full set of cohort comparisons for the asset-based analyses are in Appendix Table B.5, and the decomposition of cohort change in the Black-White difference in *total net worth* is available in Appendix Table B.6. [Back to text.]

CHAPTER 5

Conclusion

The true value in studying temporal dynamics is that differences in temporality can illuminate the process by which an exposure to inequality becomes a pattern of inequality—and the process by which patterns of inequality become stratified social systems. Each chapter of my dissertation leverages two different empirical cases—intergenerational poverty and wealth inequality—to advance our understanding of how a society becomes economically and racially stratified.

In Chapter 2, I investigated why early-childhood poverty leads to worse socioeconomic outcomes than later-childhood poverty. My study's findings challenge the dominant explanation in the social sciences, which holds that poverty is uniquely harmful for children during the earliest stages of development. Instead, I presented evidence to support an alternate explanation, whereby the same children who are exposed to poverty at younger ages tend to experience poverty for a longer share of childhood. This phenomenon—which I refer to as the cumulative dimension of timing—is evident in the case of poverty, but it can apply to any empirical context in which scholars find that timing differences are correlated with cumulative exposure.

In Chapter 3, I examined a childhood-based explanation for why socioeconomic inequalities between Black and White individuals remain so persistent over time, despite historical fluctuations and antipoverty efforts. I presented evidence to show that the racial/ethnic inequalities in childhood poverty are more extreme than we previously realized, using traditional measures. By jointly estimating the role of children's poverty rates and cumulative exposures, I found that a large share of Black–White inequality in adult income can be attributed to differences in the length of cumulative exposure to poverty. I argue that temporal exposures offer a key source of variation for explaining the persistence of population-level inequality.

In Chapter 4, I examined the historical evolution of the intergenerational drivers of wealth inequality, over the last three decades. By comparing changes in total assets, at age 35, I found that changes in socioeconomic background have reduced inequalities between Black and White individuals. However, within-cohort analyses reveal that socioeconomic background remains the largest contributor to the racialized wealth gap, regardless of time period or cohort change. My study highlights the enduring significance of socioeconomic background for explaining wealth inequalities.

5.1 Social Hierarchies and Demographic Patterns

Ultimately, temporal exposures illuminate how social hierarchies and demography are uniquely embedded. Drawing on the work of economic sociologists who have made the same observation about the economy and society (Granovetter 1985; Krippner 2004), I explore the inseparability of social hierarchies and

demographic patterns, with respect to the temporal dynamics of a person's life experiences.

Throughout my research, I advance an empirical and theoretical framework for explicitly bringing together theories of stratification and demography. Empirically, the goal is to jointly estimate the *entry* into a specific socioeconomic status (which I refer to, throughout the manuscript, as the rates of exposure) and the *amount* of time spent experiencing a given socioeconomic status or set of conditions (or, as I refer to it, the length of cumulative exposure). Theoretically, my objective is to consider how the temporality of a person's life experiences can accumulate into patterns of inequality and social hierarchy.

My work also has the potential to inform how we think about the equitable effects of social policy. I suggest that there might be potential benefits, for reducing generational inequality, by shifting our policy frameworks from a *contemporaneous* focus to a *temporally holistic* perspective; and by expanding our policy data infrastructure to identify populations at higher risk of experiencing inequality, based on records of historical and cumulative exposures to economic disadvantage. For example, in the case of poverty, resources could be targeted at individuals who are currently experiencing poverty, as well as individuals who are at the highest risk of experiencing intergenerational inequality: i.e., children who are currently experiencing poverty *and* children who have experienced recurrent exposures to poverty in the past. In doing so, we can update our policy logics to recognize both contemporaneous disadvantage (happening now) and historical disadvantage (happened in the past), in order to reduce precarity and promote social mobility, for the most vulnerable members of society.

5.2 Promise and Opportunities for Jointly Estimating Life-course Exposures and Historical Dynamics

A natural extension of my research, on temporal dynamics, is to examine the joint distribution of life-course and historical timing, in order to identify political and institutional drivers of inequality. By leveraging the joint distribution between life-course and historical dynamics, analyses can potentially identify key pathways by which political actors and institutional policies have directly affected individual-level socioeconomic outcomes.

There are three analytic domains that would be particularly well suited for this type of analysis, combining life-course exposures and historical dynamics. First, an examination of historical changes to the welfare state might be used to examine how changes to social spending have affected individual-level socioeconomic attainments across the life course. Second, the rates of change in how the economy restructured from a wage-based economy to an asset-based economy could be used to examine how macroeconomic conditions shape individual-level wealth accumulation and wealth inequality. Third, spatial variation in the levels of structural racism and other macrosocial conditions can be used to examine how sensitive individual-level outcomes are to different types of oppression. By drawing on institutional and demographic theories (from sociology, as well as political science, history, and public policy), I can investigate how these large-scale historical dynamics have affected individual-level outcomes.

5.3 The Central Importance of the Family

The family is where inequalities first present themselves. And, in many ways, families are the fundamental building blocks of society. Contemporary inequalities are generated, in part, through parental characteristics and the cumulative experiences of childhood. Historical inequalities are often transmitted through the intergenerational persistence of socioeconomic status and resources.

But, if the family is where inequalities begin to form, then this means that families may *also* serve as the site for robust social action and human flourishing.

However, the only way to undo society's social, economic, and racialized stratification is by actively seeking out remedies for historical and contemporary legacies of injustice; by seeking out families who have experienced generational inequalities; and by targeting the necessary supports to people of all ages. Because—when all is said and done—a society will never be free so long as people are permitted to inherit inequalities of the past.

APPENDIX A

Additional Figures for Chapter 2

All of the secondary figures for Chapter 2, which supplement the primary manuscript, are included on the pages that follow.

Table A.1: Childhood Poverty Matrix, by Age of Child

By each age	Number of previous years spent in poverty, prior to each age															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Probability of poverty at exact-age																
1	0.057	0.627														
2	0.046	0.378	0.762													
3	0.026	0.274	0.488	0.758												
4	0.035	0.186	0.353	0.673	0.835											
5	0.034	0.196	0.225	0.607	0.655	0.849										
6	0.021	0.146	0.237	0.389	0.598	0.806	0.867									
7	0.013	0.140	0.274	0.454	0.331	0.687	0.677	0.936								
8	0.024	0.143	0.209	0.349	0.415	0.445	0.722	0.825	0.934							
9	0.021	0.074	0.199	0.245	0.360	0.422	0.599	0.731	0.790	0.922						
10	0.018	0.071	0.182	0.283	0.208	0.430	0.446	0.466	0.720	0.815	0.935					
11	0.017	0.098	0.141	0.217	0.294	0.261	0.505	0.390	0.481	0.776	0.853	0.893				
12	0.012	0.077	0.101	0.225	0.231	0.342	0.305	0.453	0.442	0.655	0.682	0.851	0.929			
13	0.011	0.053	0.142	0.196	0.223	0.353	0.544	0.442	0.547	0.630	0.778	0.873	0.858	0.741		
14	0.015	0.062	0.126	0.170	0.174	0.252	0.454	0.402	0.580	0.514	0.646	0.576	0.796	0.626	0.793	
15	0.016	0.052	0.082	0.145	0.164	0.268	0.296	0.306	0.434	0.492	0.679	0.743	0.753	0.614	0.896	0.958
Mean years of poverty remaining, between each age and 15																
1	1.1	7.1														
2	0.8	4.3	8.1													
3	0.7	2.7	5.8	8.2												
4	0.6	1.9	4.0	6.5	8.1											
5	0.5	1.8	2.6	5.1	5.9	8.1										
6	0.3	1.4	2.7	2.9	4.8	6.0	7.8									
7	0.3	1.0	2.2	2.9	2.4	5.3	5.7	7.2								
8	0.2	0.8	1.4	2.7	2.3	3.1	4.9	5.7	6.3							
9	0.2	0.5	1.4	1.5	2.3	2.4	3.4	4.5	5.1	5.5						
10	0.1	0.5	0.9	1.6	1.2	2.4	2.7	2.7	4.1	4.5	4.8					
11	0.1	0.4	0.6	1.2	1.4	1.3	2.3	2.2	2.8	3.6	3.8	3.9				
12	0.1	0.3	0.5	0.8	0.9	1.4	1.2	1.9	2.1	2.6	2.9	3.2	3.1			
13	0.1	0.1	0.4	0.6	0.6	0.9	1.4	1.1	1.6	1.8	2.0	2.4	2.4	2.1		
14	0.0	0.1	0.2	0.4	0.3	0.5	0.7	0.8	1.1	1.0	1.2	1.3	1.6	1.3	1.7	
15	0.0	0.1	0.1	0.1	0.2	0.3	0.3	0.3	0.4	0.5	0.7	0.7	0.8	0.6	0.9	1.0
Mean years of total poverty, by age 15																
1	1.1	8.1														
2	0.8	5.3	10.1													
3	0.7	3.7	7.8	11.2												
4	0.6	2.9	6.0	9.5	12.1											
5	0.5	2.8	4.6	8.1	9.9	13.1										
6	0.3	2.4	4.7	5.9	8.8	11.0	13.8									
7	0.3	2.0	4.2	5.9	6.4	10.3	11.7	14.2								
8	0.2	1.8	3.4	5.7	6.3	8.1	10.9	12.7	14.3							
9	0.2	1.5	3.4	4.5	6.3	7.4	9.4	11.5	13.1	14.5						
10	0.1	1.5	2.9	4.6	5.2	7.4	8.7	9.7	12.1	13.5	14.8					
11	0.1	1.4	2.6	4.2	5.4	6.3	8.3	9.2	10.8	12.6	13.8	14.9				
12	0.1	1.3	2.5	3.8	4.9	6.4	7.2	8.9	10.1	11.6	12.9	14.2	15.1			
13	0.1	1.1	2.4	3.6	4.6	5.9	7.4	8.1	9.6	10.8	12.0	13.4	14.4	15.1		
14	0.0	1.1	2.2	3.4	4.3	5.5	6.7	7.8	9.1	10.0	11.2	12.3	13.6	14.3	15.7	
15	0.0	1.1	2.1	3.1	4.2	5.3	6.3	7.3	8.4	9.5	10.7	11.7	12.8	13.6	14.9	16.0

Note: The primary table with the age-specific probabilities of entering poverty, at age 6, is available in Table 2.1.

APPENDIX B

Additional Tables for Chapter 4

All of the secondary tables for Chapter 4, which supplement the primary manuscript, are included on the pages that follow.

Table B.1: Sample Characteristics, for All Three Age-35 Cohorts, by Racial/Ethnic Group

	Black men and women				White men and women			
	All	1990s	2000s	2010s	All	1990s	2000s	2010s
Total net worth, age 35 (dollars)								
Mean	65,585	38,958	166,640	33,449	224,424	215,337	249,100	215,226
Standard deviation	407,224	98,278	812,797	153,205	643,425	598,408	696,323	646,493
10th percentile	-9,608	-1,907	-6,015	-31,476	-14,078	0	-13,195	-34,331
25th percentile	0	0	8	0	7,554	20,517	5,704	835
50th percentile	7,916	8,296	12,300	3,413	66,686	80,179	65,273	49,880
75th percentile	45,110	38,518	48,543	49,397	207,986	194,480	218,786	209,980
90th percentile	116,308	115,593	158,638	111,778	496,231	451,821	624,649	516,599
Total assets, age 35 (dollars)								
Mean	111,217	67,059	235,244	81,347	362,421	306,232	394,098	395,856
Standard deviation	458,697	129,161	899,788	199,194	712,924	606,525	727,102	794,631
10th percentile	0	0	7	0	4,902	8,233	4,563	3,579
25th percentile	1,298	893	3,472	971	31,069	49,650	25,366	21,919
50th percentile	16,079	16,450	28,518	12,692	186,297	172,511	207,688	193,400
75th percentile	91,383	97,978	159,897	75,760	407,972	346,129	456,290	439,703
90th percentile	242,715	187,567	400,152	276,053	790,165	620,905	900,342	885,257
Total debts, age 35 (dollars)								
Mean	44,959	28,101	65,794	47,812	140,089	96,127	153,469	174,768
Standard deviation	93,502	59,780	116,073	100,250	191,056	110,642	184,671	244,346
10th percentile	0	0	0	0	0	0	0	0
25th percentile	0	0	0	0	8,333	8,627	9,840	7,158
50th percentile	2,267	2,136	3,472	1,650	80,358	62,426	103,318	98,998
75th percentile	38,680	20,706	91,660	35,792	197,588	143,418	224,985	242,663
90th percentile	153,625	104,650	238,873	177,212	343,319	236,970	377,752	403,609
Socioeconomic background								
Grew up in the South	0.57	0.59	0.58	0.56	0.24	0.21	0.27	0.25
Low birth weight	0.08	0.07	0.09	0.09	0.05	0.06	0.04	0.05
Parents were married, adolescence	0.47	0.57	0.48	0.37	0.85	0.88	0.85	0.81
Two birth parents, adolescence	0.37	0.45	0.43	0.26	0.79	0.85	0.78	0.72
Mother employed, adolescence	0.55	0.43	0.60	0.62	0.77	0.84	0.67	0.76
Father employed, adolescence	0.85	0.83	0.83	0.89	0.93	0.95	0.92	0.92
Parents owned their home, adolescence	0.45	0.49	0.43	0.43	0.83	0.85	0.82	0.82
Parents in poverty, adolescence	0.51	0.54	0.50	0.49	0.10	0.09	0.10	0.13
Parents' family income, adolescence (dollars)	51,839	46,327	50,950	56,912	258,809	435,959	184,305	134,451
Mother's years of education	12.0	10.7	12.0	13.1	13.3	12.5	13.2	14.1
Father's years of education	11.1	9.3	11.5	12.3	13.4	12.7	13.5	14.1
Mother's age at birth	25.5	27.7	24.5	24.1	26.9	27.4	25.9	27.1
Father's age at birth	30.8	33.9	29.2	29.0	29.5	30.1	28.7	29.6
Number of siblings	3.3	4.3	3.6	2.3	2.3	2.9	2.0	1.8
Demographic characteristics								
Female	0.57	0.66	0.58	0.49	0.51	0.51	0.51	0.51
Birth year	1970.6	1958.4	1969.5	1981.3	1969.4	1958.3	1969.4	1980.6
1990s Decade	0.35	1.00	0.00	0.00	0.37	1.00	0.00	0.00
2000s Decade	0.23	0.00	1.00	0.00	0.27	0.00	1.00	0.00
2010s Decade	0.42	0.00	0.00	1.00	0.36	0.00	0.00	1.00
Unweighted N	2,512	1,024	491	997	3,425	1,329	815	1,281

Note: The primary abridged version of these statistics can be found in the main manuscript, in Table 4.1.

Table B.2: Decomposition of the Cohort Change in Total Assets, for Each Racial/Ethnic Group

	Decomposition of the cross-cohort difference in mean assets					
	1990s – 2000s		2000s – 2010s		1990s – 2010s	
	Dollars	Percent	Dollars	Percent	Dollars	Percent
PANEL 1: Total population of men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	-10,731	-8.5	-49,555	101.0	-20,568	-26.7
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	-144	-0.1	17,559	-35.8	-8,969	-11.7
Cohort change in all regression coefficients (Components A2+B2+C)	136,907	108.6	-17,085	34.8	106,488	138.4
Total cohort change in mean assets	126,033	100.0	-49,081	100.0	76,952	100.0
PANEL 2: Black men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	151,906	90.3	-17,859	11.6	177,324	>1000
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	1,791	1.1	23,807	-15.5	3,450	24.1
Cohort change in all regression coefficients (Components A2+B2+C)	14,488	8.6	-159,844	103.9	-166,486	<-1000
Total cohort change in mean assets	168,185	100.0	-153,896	100.0	14,288	100.0
PANEL 3: White men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	-43,125	-49.1	-41,726	<-1000	-44,315	-49.4
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	331	0.4	3,134	178.2	-3,703	-4.1
Cohort change in all regression coefficients (Components A2+B2+C)	130,660	148.7	40,350	>1000	137,643	153.6
Total cohort change in mean assets	87,866	100.0	1,759	100.0	89,624	100.0

Note: The primary decomposition of total assets is available in Table 4.2, and the decomposition of the cohort change in *total net worth* is available in Appendix Table B.3.

Table B.3: Decomposition of the Cohort Change in Total Net Worth, for Each Racial/Ethnic Group

	Decomposition of the cross-cohort difference in mean net worth					
	1990s – 2000s		2000s – 2010s		1990s – 2010s	
	Dollars	Percent	Dollars	Percent	Dollars	Percent
PANEL 1: Total population of men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	-7,612	-12.6	-33,875	65.2	-14,586	-171.1
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	-657	-1.1	10,983	-21.1	-7,366	-86.4
Cohort change in all regression coefficients (Components A2+B2+C)	68,730	113.7	-29,045	55.9	30,477	357.5
Total cohort change in mean net worth	60,462	100.0	-51,936	100.0	8,525	100.0
PANEL 2: Black men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	70,246	55.0	-30,845	23.2	79,787	<-1000
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	1,543	1.2	23,723	-17.8	3,176	-57.7
Cohort change in all regression coefficients (Components A2+B2+C)	55,893	43.8	-126,069	94.7	-88,473	>1000
Total cohort change in mean net worth	127,682	100.0	-133,191	100.0	-5,509	100.0
PANEL 3: White men and women						
Explained by socioeconomic background:						
Cohort change in socioeconomic background, means (Component A1)	-32,921	-97.5	-35,850	105.8	-33,297	>1000
Unexplained by socioeconomic background:						
Cohort change in demographic composition, means (Component B1)	87	0.3	6,997	-20.7	-1,176	>1000
Cohort change in all regression coefficients (Components A2+B2+C)	66,596	197.3	-5,021	14.8	34,361	<-1000
Total cohort change in mean net worth	33,762	100.0	-33,874	100.0	-112	100.0

Note: The primary decomposition of total assets is available in Table 4.2, and the full set of cohort comparisons for the asset-based analyses are available in Appendix Table B.2.

Table B.4: Decomposition of the Black-White Difference in Total Net Worth, Across Cohorts

	Decomposition of the racial/ethnic difference in mean net worth	
	Black – White	
	Dollars	Percent
PANEL 1: Black and White individuals, 1990s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-231,747	131.4
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	3,451	-2.0
Difference in all regression coefficients (Components A2+B2+C)	51,917	-29.4
Total difference in mean net worth by racial/ethnic group	-176,379	100.0
PANEL 2: Black and White individuals, 2000s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-205,680	249.4
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	-2,583	3.1
Difference in all regression coefficients (Components A2+B2+C)	125,803	-152.6
Total difference in mean net worth by racial/ethnic group	-82,459	100.0
PANEL 3: Black and White individuals, 2010s		
Explained by socioeconomic background:		
Difference in socioeconomic background, means (Component A1)	-97,585	53.7
Unexplained by socioeconomic background:		
Difference in demographic composition, means (Component B1)	5,920	-3.3
Difference in all regression coefficients (Components A2+B2+C)	-90,112	49.6
Total difference in mean net worth by racial/ethnic group	-181,777	100.0

Note: The primary decomposition of total assets is available in Table 4.3.

Table B.5: Decomposition of Cohort Change in the Black-White Difference in Total Assets, Across Cohorts

	Decomposition of the cohort change in the racial/ethnic difference in mean assets	
	$(B - W)_{T1} - (B - W)_{T0}$	
	Dollars	Percent
PANEL 1: Black and White individuals: 2000s – 1990s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	28,620	35.6
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	-5,216	-6.5
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	56,915	70.9
Total cohort change in the total difference in mean assets by racial/ethnic group	80,319	100.0
PANEL 2: Black and White individuals: 2010s – 2000s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	94,356	-60.6
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	6,439	-4.1
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	-256,450	164.8
Total cohort change in the total difference in mean assets by racial/ethnic group	-155,655	100.0
PANEL 3: Black and White individuals: 2010s – 1990s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	122,976	-163.2
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	1,223	-1.6
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	-199,535	264.9
Total cohort change in the total difference in mean assets by racial/ethnic group	-75,336	100.0

Note: The primary decomposition of total assets is available in Table 4.4, and the decomposition of the cohort change in Black-White difference in *total net worth* is available in Appendix Table B.6.

Table B.6: Decomposition of Cohort Change in the Black-White Difference in Total Net Worth, Across Cohorts

	Decomposition of cohort change in the racial/ethnic difference in mean net worth	
	$(B-W)_{T1} - (B-W)_{T0}$	
	Dollars	Percent
PANEL 1: Black and White individuals: 2000s – 1990s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	26,067	27.8
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	-6,034	-6.4
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	73,887	78.7
Total cohort change in the total difference in mean net worth by racial/ethnic group	93,920	100.0
PANEL 2: Black and White individuals: 2010s – 2000s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	108,095	-108.8
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	8,503	-8.6
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	-215,916	217.4
Total cohort change in the total difference in mean net worth by racial/ethnic group	-99,317	100.0
PANEL 3: Black and White individuals: 2010s – 1990s		
Explained by socioeconomic background:		
Cohort change in the difference in socioeconomic background, means (Component A1)	134,162	<-1000
Unexplained by socioeconomic background:		
Cohort change in the difference in demographic composition, means (Component B1)	2,469	-45.7
Cohort change in the difference in all regression coefficients (Components A2+B2+C)	-142,029	>1000
Total cohort change in the total difference in mean net worth by racial/ethnic group	-5,398	100.0

Note: The primary decomposition of total assets is available in Table 4.4, and the full set of cohort comparisons for the asset-based analyses are available in Appendix Table B.5.

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