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Abstract

Grounded in theories of intersectionality and cumulative (dis)advantage, we develop complementary formalizations of (dis)advantage: one that captures the traditional practice of studying *Cumulative (Dis)Advantage* (CDA) that reflects inequalities in outcomes and *Opportunity-Weighted CDA* that additionally accounts for inequalities in opportunities. We study the properties of these (dis)advantages and show that traditional cumulative disadvantage and advantage are mutually exclusive; this is not true of opportunity-weighted CDA. Using these formalizations, we analyze the Health and Retirement Study (1998-2018) to assess how total life expectancy at age 50 is associated with the accumulation of racial/ethnic, nativity, gender, early-life, and educational (dis)advantages. We find that the benefits and penalties of one (dis)advantage depend on positionality on the other axes of inequality. Whites ubiquitously experience *Cumulative Advantage*: they benefit more from having higher education than Blacks and Latinx. However, when accounting for racial/ethnic inequities in educational attainment, results predominantly show *Opportunity-Weighted Cumulative Disadvantage* for Blacks and Latinx. Finally, we present a specification curve analysis that includes early-life adversity. Our contributions include the formalization (a mathematical grounding) of two CDA approaches – traditional and one that incorporates inequities in *opportunities* – and empirical results that comprehensively document the intersecting axes of stratification that perpetuate health inequities.

Keywords: intersectionality, cumulative (dis)advantage, life expectancy, health disparities, social stratification

1 Introduction

A historic, yet enduring question in sociology with far reaching policy implications is to understand the ways in which social stratification—whether defined by race/ethnicity, gender, socioeconomic status, or other characteristics—affect life outcomes, including health. In recent decades, theoretical developments and data availability has nuanced this question into how positionality on multiple axes of stratification accumulate across the life course to influence health. Two frameworks have become prominent in this literature: *intersectionality* and *cumulative (dis)advantage*.

Intersectionality arose from legal studies and Black feminist theory and focuses on how recursive power relations and the social structures in which they are embedded intersect to create and perpetuate complex social inequities (Collins 2015; Crenshaw 1989). Cumulative (dis)advantage has its roots in sociology and provides specific predictions on the accumulation of (dis)advantage, as itself or as it relates to various life outcomes such as good health (Dannefer 1987; Merton 1968, 1988). A main distinction between intersectionality and cumulative (dis)advantage is that while cumulative (dis)advantage is most often, though inconsistently (Dannefer 2018; Ferraro and Morton 2018), understood as processual, articulations of intersectionality do not necessarily have a temporal component. Nevertheless, intersectionality and cumulative (dis)advantage are not oppositional, but complementary, in that both emphasize the centrality of social hierarchies in shaping inequities.

We begin by introducing and historicizing the concepts of intersectionality and cumulative (dis)advantage. We then formalize the concept of cumulative (dis)advantage as it is traditionally used in the literature, which we will name, simply, “CDA”. Next, we develop a complementary definition of cumulative (dis)advantage that takes as its central tenet that social stratification results in the disproportionate accumulation of (dis)advantage to the already (dis)advantaged, limiting (in the case of the disadvantaged) or promoting (in the case of the advantaged) access to opportunities across the life course (Pais 2014; Sharkey 2013; Tilly 1998; Williams and Mohammed 2013). For example, low social mobility continues to characterize many high-income societies, so we propose a CDA that incorporates different probabilities that members of distinct social groups (e.g., Black vs. White) have of acquiring an additional (dis)advantage (e.g., low vs. high education). We call this new formalization: "Opportunity-Weighted Cumulative (Dis)advantage" (CDA-OW). Finally, we use the Health and Retirement Study (RAND Center for the Study of Aging 2022; University of Michigan 2017) to demonstrate both traditional CDA and CDA-OW life expectancy. We show how race/ethnicity, nativity for Latinx, gender, early-life adversity, and educational attainment accumulate across the life course to produce inequities in life expectancy.

2 Conceptualizing and modeling power and privilege

2.1 Intersectionality

Over the last twenty years, the term intersectionality has become increasingly prevalent across the social sciences in part because it resonates with our own lived experience (Davis 2008). Even prior to the use of the term, the underlying concept was not uncommon, especially amongst Black womanist and feminist thinkers ("Ain't I a Woman" by Sojourner Truth could be considered one of the most famous examples). The term itself is often de-historicized, and so we offer a brief background.

Legal scholar Dr Kimberlé Crenshaw, who coined the term, took as examples three legal cases wherein companies were accused of employment discrimination against Black women (Crenshaw

1989). The gist of the companies' defense was that they were not guilty because – even though they were accused of not employing/promoting "Black women" – they did employ and promote Blacks (who were men) and women (who were White); i.e., they treated race and gender separately. Crenshaw argued that the court must consider status on each axis simultaneously, as they function in the real world. One is neither Black first, nor woman first, but both together, always.

As such, intersectionality's major contribution is the insight that power relations cannot be understood by focusing on a single axis of inequality (Bauer 2014) and that without this intersectional understanding, inequities will persist (Collins 2015; Crenshaw 1994). Since its conceptualization, intersectionality has moved beyond the courtroom, and now is often used to provide a framework for understanding how social positionalities intersect to create exposures to advantages and disadvantages that affect a range of both opportunities and life outcomes, including health (Bowleg 2021; Green, Evans, and Subramanian 2017; Hankivsky 2012).

As an analytical project, intersectionality can be thought of as the study of how structures of oppression that include ascribed (e.g., race/ethnicity) and achieved (e.g., education) characteristics intersect to expose individuals to a balance of benefit and risk in the form of access to resources, including human, cultural, and economic capital (Cho, Crenshaw, and Mccall 2013). How to study intersectionality empirically is a topic of animated debate (Bowleg 2021; Gkiouleka et al. 2018). Our reading of Crenshaw and colleagues is that intersectionality should be understood as "an analytic sensibility," and no methodological tool is "inherently antithetical (or central) to the enterprise" (Cho et al. 2013:795-796).

As such, it is important to clarify our use of the concept. Intersectionality does not “estimate the collective impact of gender, race, and class—measured as several simple binaries—as the sum of their independent effects (e.g., gender + class + race/ethnicity)” (Hankivsky 2012 p. 1713). It does not make specific predictions about the direction or intensity of the interactive effects (Bowleg 2021; Gkiouleka et al. 2018). Rather, it emphasizes a dependency in the impacts—an “interaction.” Contemplating the ways in which these axes of inequality intersect leads directly to theories of cumulative (dis)advantage.

2.2 Cumulative (dis)advantage

Cumulative (dis)advantage offers an important additional insight. Both intersectionality and CDA point to positionality vis-à-vis power structures structuring lives (Bourdieu 1984), but CDA is more often used to describe a *temporal* process, operating across the life course, that leads to widening disparities in outcomes over age as negative (or positive) exposures accumulate (Dannefer 2018; DiPrete and Eirich 2006; Ferraro and Morton 2018; Pais 2014). This temporal element existed from the conception of cumulative advantage as the “Matthew effect,” based on a sociological study of how publications, awards, and citation counts between scientists diverged over time, advantaging the already-advantaged (Merton 1968). Since the 1960s, cumulative advantage has birthed its opposite and equally intuitive concept of “cumulative disadvantage,” which was productively merged with the life course literature in the 1980s (Crystal and Shea 1990; Dannefer 1987), and is used in many applied contexts including health research (Dannefer 2018; Willson, Shuey, and Elder Jr. 2007). As Ferraro and Kelley-Moore (2003:708) write,

> Cumulative disadvantage theory emphasizes how early advantage or disadvantage is critical to how cohorts become differentiated over time. Not only do the early risk factors shape

> trajectories in the short-term outcomes but in the long-term outcomes as well. The effects of risk factors accumulate over the life course, thereby increasing heterogeneity in later life.

As there are several comprehensive reviews of cumulative (dis)advantage theory, we will not go into great depth with regard to its evolution. However, it is important to note that the terms of cumulative (dis)advantage are often defined within the context of each specific study, leading to a distinct lack of consistency. DiPrete and Eirich (2006:280) bemoan,

> The frequent lack of clarity in models, mechanisms, and tests is a continuing issue in the sociological literature on CA [cumulative advantage] processes as potential generators of inequality. This lack of clarity can produce incorrect specifications, incorrect estimates, and incorrect interpretations.

They outline two main types of approaches: "strict CA" versus the "Blau-Duncan approach" (DiPrete & Eirich 2006:273). Within strict CA, original empirical analyses of cumulative advantage involved studying how a person's advantages in some resource accrue across time, widening inequalities. This can operate in what they term a "simple" way: having a resource (e.g., wealth) tends to generate more of that resource. Or, it can be "path-dependent," as in Merton's (1968) piece: scientific success breeds success indirectly, through the accrual of resources (e.g., grants) that enable productivity. In sum, both simple and path-dependent are "strict" formulations according to DiPrete and Eirich, meaning that there is a single resource (think education, wealth, or citations) where "future accumulation depends on current accumulation" and the question is whether inequality grows proportionally or in some other form over time (p. 273).

However, the "Blau-Duncan approach" – referring to Peter Blau and Otis Duncan's development of the Status Attainment Model – broadens CA to include status-resource interactions. This approach is more complicated in that instead of just looking at, e.g., the accrual of wealth based on wealth, it takes into consideration additional factors. For example, it predicts additional disadvantages will result in stronger deleterious effects on a life outcome from each disadvantage status relative to those who are disadvantaged along fewer dimensions. It is much more similar to ideas of intersectionality than the original definition of CA in the strict, Mertonian sense of temporal accumulation of a single resource (Ferraro, Schafer, and Wilkinson 2016; Mehta and Preston 2016).

The literature thus includes both varying and loose definitions of CDA, leaving open a large space of alternative interpretations. Moreover, most work does not address the difference between (dis)advantage as measured on absolute versus relative scales, an issue upon which we elaborate below (DiPrete and Eirich 2006). This lack of consistency becomes problematic in interpreting the theoretical/conceptual implications of empirical analyses. For example, Hale (2017) assumes that cumulative disadvantage and cumulative advantage always co-exist, that is, evidence for cumulative disadvantage for Blacks is evidence for cumulative advantage for Whites, which is akin to Merton's original conception:

> The practice of giving unto everyone that hath much while taking from everyone that hath little will lead to the rich getting forever richer while the poor become poorer. Increasingly absolute and not only relative deprivation would be the continuing order of the day. (Merton 1988:609-610)

An important insight to be gleaned from Merton's quotation above is that the underlying principle of the Matthew effect (the foundation of cumulative (dis)advantage) is that (dis)advantages are likely to accrue to those who are already (dis)advantaged (the rich get richer and the poor, poorer). Indeed, there is a large body of research showing that across societies both opportunities and outcomes are structured by, e.g., origin-family socioeconomic status (SES), gender, race/ethnicity, nativity, and geography (Bourdieu 1984; Conley 1999; Pais 2014; Sharkey 2013; Tilly 1998; Williams and Mohammed 2013).

However, neither the strict Mertonian nor the Blau-Duncan approach take into consideration the *probabilities* of accumulating another (dis)advantage. In other words, one typical empirical application of cumulative (dis)advantage in the literature studies intersections of gender × race × education and estimates the outcome of cognitive health expectancies comparing *if* a Black Early Baby Boomer achieves higher education compared to a White Boomer, but it does not factor in that the likelihood of that attainment is so much lower (Hale et al 2020). We argue that cumulative disadvantage should also take into consideration opportunity—this allows our empirical analyses to more closely align with the original theoretical conceptualization. As such, we set forth a novel concept "Opportunity-Weighted Cumulative (Dis)Advantage" (CDA-OW) (in Section 2.2.3) as an important addition to the traditional cumulative disadvantage literature.

In order to ensure clarity in our concepts and interpretation, we clearly define cumulative advantage and disadvantage, specifically discussing two key elements: 1) the difference between traditional CDA and opportunity-weighted CDA, 2) measurement on absolute versus relative scales.

We first formalize the concepts of CDA and opportunity-weighted CDA and illustrate the interplay among the two elements. This approach allows us to deliver definitional clarifications that are critical, as the existing literature shows there is much confusion about the nature of cumulative (dis)advantage. We then illustrate how measurement scale matters in understanding health inequities. Health inequities are often evaluated in terms of absolute differences, for example, in terms of life expectancy. Examining both absolute and relative disparities, however, can further our understanding of the lived experience of health burdens. For example, Montez and Hayward (2014) found that Black women who had advantaged childhoods have eight more years of active healthy life expectancy than their disadvantaged counterparts, whereas White women with advantaged childhoods have nine years more than their disadvantaged counterparts. This appears to indicate that White women experience one-year additional advantage from having no childhood adversities. However, comparing the gain (or loss) in *proportional* terms shows that the share of active life expectancy lost attributable to childhood adversity (or gained if there are no adversities) is similar for Black and White women.

2.2.1 Cumulative (Dis)advantage and Opportunity-Weighted Cumulative (Dis)Advantage

We provide both a heuristic description of the two complementary definitions of cumulative (dis)advantage, the traditional definition (CDA) and the one that takes into consideration the probability of accumulating an additional (dis)advantage given the first (dis)advantage—opportunity-weighted CDA (CDA-OW), three related insights, and an explicit, mathematical definition. We do this using as an example two risk factors for poor health: race/ethnicity (Black and White) and education (low and high).[1] The "reward" is strictly positive, for example, life expectancy, such that more is better.

Our first conceptualization of CDA is as it is typically used in the literature, regardless of whether it is the strict or Blau-Duncan approach, as in, it does not take into consideration the probability of accruing a resource or accumulating an additional (dis)advantage. For our intersectional (Blau-Duncan) approach, the traditional framing is based on the question: among those who have one advantage (White compared to Black), does gaining an additional advantage (high education v. low) result in more or less gain in life expectancy, than for those who do not have the first advantage? We can understand this as a conditional statement that is focused only on the outcome, and so will refer to it as "conditional" and "outcome-focused": do Whites gain more from high education than Blacks, conditional on both having the outcome of high education? Under this outcome-focused definition, cumulative *advantage* arises if an average White person gains more from high education than an average Black person; cumulative *disadvantage* arises if an average Black person loses more from low education than an average White person.

The first insight and a key feature of the outcome-focused definition is that cumulative advantage is the antithesis of cumulative disadvantage: evidence for one is evidence contra the other. If Whites gain more from higher education relative to Blacks, it means that Blacks lose less from lower education relative to Whites. In other words, compared to each other, either Whites gain more from higher education (cumulative *advantage*) *or* Blacks lose more from lower education (cumulative *disadvantage*). Both cannot be true. We provide a mathematical formulation of this below (Section 2.2.3.1).

A second insight and a key feature of the opportunity-weighted definition of cumulative (dis)advantage is that the existence of one does not imply anything about the existence of the other. That is, cumulative disadvantage and cumulative advantage may or may not co-exist. The data may also support neither advantage nor disadvantage. We prove this formally below in Section 2.2.3.2, but conceptually: our definition of opportunity-weighted cumulative (dis)advantage factors in the likelihood of attaining additional (dis)advantages. Under this definition, we weigh the loss from one disadvantage (low education) with the likelihood of attaining low education and ask whether the already disadvantaged (Blacks) have a greater expected loss from lower education – calculated as the probability of experiencing the disadvantage times the magnitude of the disadvantage. The converse is true for cumulative advantage: Whites are more likely to have higher educational attainment, thus the question is, weighting for that higher probability of an additional advantage (high education), do the already privileged (Whites) gain more from high education. Under this opportunity-weighted definition, cumulative disadvantage arises if the probability-weighted loss from low education is greater for Blacks than Whites; cumulative advantage arises if the probability-weighted gain from higher education is greater for Whites than Blacks.

These two conceptualizations of cumulative (dis)advantage are complementary. Analyzing both types of cumulative (dis)advantage characterizes health inequities more comprehensively than only using one of the approaches.

2.2.2 Measurement Scales

Our third insight is based on measurement scales. Both absolute and relative scales can be used to describe cumulative (dis)advantage. Research has not analyzed under what conditions the two measurement scales produce the same qualitative conclusion, that is, whether the data support cumulative advantage or cumulative disadvantage.

We show that for outcome-focused CDA, some invariance exists across measurement scales: cumulative disadvantage on the absolute scale always implies cumulative disadvantage on the relative scale; and cumulative advantage on the relative scale always implies cumulative advantage on the absolute scale. For other combinations discordance is possible. For example, if there is cumulative advantage on the absolute scale, there may be either cumulative advantage or disadvantage on the relative scale. For the opportunity-weighted measure we present the results only on the absolute scale on which interpretation is straightforward. The relative scale requires comparing probability-weighted ratios, similar to what population-attributable fraction calculations involve. However, elaborating the similarities and differences between CDA-OW and population attributable fraction is beyond the scope of this paper.

2.2.3 Formal Notation for CDA

[Boxes 1 and 2]

Here we formalize mathematically both CDA and CDA-OW. Boxes 1 and 2 summarize the settings described above. The two-dimensional crosstabulations are (i) the levels of the outcome and (ii) for the opportunity-weighted definition, the population fractions in each of the cells. A is the level of the outcome for low-educated Blacks, B for high-educated Blacks, C low-educated Whites, and D high-educated Whites; a, b, c, d are the matching population fractions. B-A and D-C are the difference in the outcome between high- and low-educated for Blacks and Whites, respectively. We call these, depending on the context, loss from lower education or gain from high education.

2.2.3.1 Cumulative Disadvantage: Outcome-focused

Cumulative disadvantage is a relationship between the two risk factors such that the disadvantaged lose more from having an additional disadvantage compared to the advantaged. Box 1 shows that the loss from lower education for Blacks, on an absolute scale, is B-A and for Whites D-C. Cumulative disadvantage is then defined by the condition, (B-A) > (D-C): The loss in magnitude in an absolute sense is larger for Blacks, compared to Whites.

Cumulative advantage is a relationship between the two risk factors such that the advantaged gain more from having an additional advantage compared to the disadvantaged. In Box 1, this relation would be that Whites gain more from high education compared to Blacks. Formally, it would be (D-C) > (B-A).

The dependence inherent in a 2X2 table also implies that the racial penalty associated with being Black is larger among the low educated compared to the high educated (C-A > D-B) under cumulative disadvantage[2]. Conversely, under cumulative advantage, the racial benefit associated with being White is larger among the high educated compared to the low educated (D-B > C-A).

Thus, cumulative disadvantage means no cumulative advantage; cumulative advantage means no cumulative disadvantage.[3]

The consideration thus far is based on a comparison of absolute (additive) differences. Researchers, however, often compare differences on a relative scale (e.g., proportionate changes, relative risks, hazard ratios). On a relative scale, we can define cumulative disadvantage as *Blacks losing proportionately more life expectancy than Whites from having a low education*. This statement translates into (B-A)/B > (D-C)/D, which reduces to B/A > D/C.[4] Cumulative advantage on the relative scale is D/C > B/A. As with the absolute scale, traditional cumulative disadvantage and cumulative advantage are mutually exclusive, evidence for one is evidence against the other. These relationships are summarized in Box 1.

As is well known, conclusions based on the absolute (additive) scale may not translate to the relative (multiplicative) scale and vice versa (Mehta and Preston 2016, Mehta et al. 2019). In our scenario, a finding of cumulative disadvantage on the relative scale does not imply a finding of cumulative disadvantage on the absolute scale. The relation could be cumulative disadvantage, cumulative advantage, or null on the relative scale. Similarly, a finding of cumulative advantage on the absolute scale may be consistent with cumulative advantage, cumulative disadvantage, or null on the relative scale. The two cases where consistency holds are as follows: first, when the data supports CD on the absolute scale, it will also support CD on the relative scale; and second, if the data supports CA on the relative scale, it will also support CA on the absolute scale.

We prove the first consistency directly and the other by contradiction. Cumulative disadvantage on the absolute scale means that B-A>D-C. This implies A/B<C/D (relative scale definition):

$$B - A > D - C \;\Rightarrow\; \frac{B}{A} > \frac{D}{C} \tag{1}$$

The proof is simply:

$$\frac{B}{A} = \frac{A + (B - A)}{A} > \frac{A + (D - C)}{A} = 1 + \frac{D - C}{A} > 1 + \frac{D - C}{C} = \frac{C + D - C}{C} = \frac{D}{C} \tag{2}$$

where step 2 follows from CD on the absolute scale. In step 4, one of the underlying assumptions for positive outcome measures, $A < C$, was used (see Box 1).

The second consistency – CA on the relative scale means CA on the absolute scale – can be shown by contradiction. Assume that we have CA on the relative scale and CD on the absolute scale. This, however, is not possible – we have proven in eq. (2) that CD on the absolute scale always implies CD on the relative scale. Hence CA on the relative scale must also imply CA on the absolute scale. The reverse does not hold: CA on the absolute scale may be associated with CA or CD on the relative scale.

2.2.3.2 Opportunity-Weighted CDA (CDA-OW)

CDA-OW incorporates the probability of attaining a status (e.g., high educational attainment) and magnitude of disadvantage into the definitions of cumulative disadvantage and cumulative advantage. Under CDA-OW, cumulative disadvantage is defined as $P_A*(B-A) > P_C*(D-C)$ where P_A is the fraction of Blacks who have low education and P_C is the fraction of Whites who have low education. Similarly, cumulative advantage is $P_B*(B-A) < P_D*(D-C)$, where P_B and P_D denote the high-educated fractions for Blacks and Whites, respectively. Here, those already privileged – Whites – have a higher expected gain from high education than Blacks.

Under CDA-OW, the data can support both cumulative disadvantage and cumulative advantage, neither of them, or only one. In contrast to the traditional definition, in which support for one (CD or CA) is evidence against the other, in the opportunity-weighted case, we cannot infer anything about OW-CD/OW-CA, even if we know that one form of OW-CD or OW-CA exists.

Note that the traditional (or outcome-focused) and opportunity-weighted definitions do not map onto each other. The incorporation of probabilities in the opportunity-weighted definition means that there is no straightforward mapping between the two definitions.

2.2.4 Temporal Accumulation

Both definitions have different implications on whether the process of accumulation is considered temporal or not and provide complementary perspectives to (dis)advantage. Using cumulative disadvantage as the example, consider first the opportunity-weighted definition that asks: given one disadvantage, what is the likelihood of experiencing another one, and how much would one lose from that additional disadvantage? How does this expected loss compare to those who start from an advantaged position? These questions are strictly rooted in temporal thinking and thus are most useful when the temporal ordering is evident, as in across a life course, e.g., ascribed characteristics such as gender and race precede educational attainment.[5] The opportunity-weighted definition therefore corresponds to the temporal formulation of the cumulative (dis)advantage concept, much as Merton's original conception (1968, 1988).

The traditional (outcome-focused) definition, in contrast, starts from a point in time in which individuals are already positioned in the dimensions of advantage and disadvantage. In our example, some Blacks have high, others low education, and the same for Whites. We ask: now that individuals have their characteristics, some advantageous others not, do those who as a group are privileged (Whites) benefit more if they have an additional advantage (high education) compared to those who are disadvantaged (Blacks)? We do not consider how, when, or if additional (dis)advantages accumulate; they are there; they are contingent. Thus, the outcome-focused definition is not necessarily rooted in a temporal perspective (imagine, for example, an analysis that studies only race and gender) and allows us to consider cumulative (dis)advantage from the perspective of what is. Traditional CDA, thus, may be considered more aligned with the "Blau-Duncan," status-resource interaction approach even though this formalization is traditionally used for strict Mertonian analyses as well (DiPrete and Eirich 2006).

2.2.5 Additive versus multiplicative processes

Cumulative (dis)advantage is sometimes framed in terms of additive versus multiplicative processes (Mehta and Preston 2016) in a way that corresponds to regression interactions and can easily be mapped onto our definition of cumulative (dis)advantage. The direction of the regression interaction – either magnifying or attenuating the disadvantage of the already disadvantaged – reveals whether the data support cumulative disadvantage or advantage. The “additive versus multiplicative” concept can further be extended to the opportunity-weighted definition of cumulative (dis)advantage by weighting the interaction coefficients with appropriate probabilities of acquiring an additional (dis)advantage.

However, while there is some resemblance between the additive/multiplicative and cumulative (dis)advantage, the important point to note is that the “additive versus multiplicative” concept in itself does not imply a direction of (dis)advantage. Consider multiplicative – this is, without inspection of the direction of the multiplicative effects, uninformative. “Additive,” on the other hand, in practice means lack of statistical significance for the interaction on the additive scale, which may be due to small differences or inadequate power.

In sum, the concept of cumulative (dis)advantage is rarely developed thoroughly and transparently in the literature. We do not suggest a solitary “correct” approach to understanding cumulative (dis)advantage, but have aimed to clarify how analyzing multiple dimensions can contribute to our understanding of health inequities, as well as inequities on other life outcomes. Our empirical analysis elaborating these concepts focuses on life expectancy as an age-old outcome of the accumulation of (dis)advantage across a life course or even a static accumulation, as through an intersectional lens.

2.3 Health through the lenses of intersectionality and cumulative (dis)advantage

We do not spend many words on the social, also termed sociopolitical (Mackenzie et al. 2020), determinants of life expectancy, as these associations have been reviewed regularly across the decades (see Gutin and Hummer 2021 for a recent review). Suffice it to say, there are reams of paper demonstrating that being Black compared to White, US-born Latinx, or Asian in the US, exposure to more early life adversities, and having lower education is associated with higher mortality (e.g., Friedman et al. 2015; Link and Phelan 1995; Miech et al. 2011; Montez and Hayward 2014; Williams and Mohammed 2013). Women, though socially disadvantaged and in poorer health (Homan 2019), consistently have longer life expectancies than their men counterparts (Lorber and Moore 2002).

Grounded in theories of intersectionality and cumulative (dis)advantage, we assume these one-dimensional risk factors have meaningful interactions. Some of this research does exist and suggests that Black Americans and Mexican Americans do not gain as much protection from higher SES as White Americans with regard to low birth weight, infant mortality, and mortality due to certain cancers (e.g., Brown 2018; Geronimus et al. 2010). This necessarily implies that White Americans gain a larger health advantage from higher SES compared to Black and Mexican Americans—cumulative advantage in our terms. Again, this is the antithesis of cumulative disadvantage, as it mathematically requires that Blacks/Latinx do not lose more from lower education.

Our project here is to use intersectionality and cumulative (dis)advantage as theoretical frameworks to discover how positionality across four primary axes of inequality (gender, race/ethnicity, childhood adversity, and education) is associated with total life expectancy—even if we must acknowledge that intersecting categories can only provide a pencil sketch of a much more colorful, textured story (Collins 2015; Crenshaw 2011).

3 Data and Methods

3.1 Data

We use the HRS, a nationally representative longitudinal survey of U.S. residents aged over 50 and their spouses. The HRS is funded by the National Institute on Aging (grant number NIA U01AG009740) and conducted by the University of Michigan (RAND Center for the Study of Aging 2022; University of Michigan 2017). Biennially, a broad range of information on demographics, family, health, and wealth is collected. We use RAND Version 2018-V1 of the HRS, which covers the years up to 2018.

Our first wave is from 1998, the year in which the addition of the 1924-30 ("Children of the Depression") and 1942-47 ("War Babies") cohorts made the HRS fully representative of the population over the age of 50 years. An unusual aspect of the current analysis, due to the focus on mortality, is that our sample includes survey nonresponses, as long as the mortality status of the respondent was ascertained and the information on gender, race/ethnicity, and education, as well as data on childhood adversities (section 4.3) is available. The resulting sample comprises 36,226 individuals and 239,053 person-waves spanning years 1998 to 2018.

3.2 Variable definitions

The set of independent variables consists of gender, reported as binary (woman/man) by the HRS, race/ethnicity, educational attainment, exact age at interview, and childhood adversities. We combine self-reported information on race/ethnicity into Non-Hispanic White, African American/Black (Hispanic or non-Hispanic) (following Chinn and Hummer 2016), Non-Black Hispanic, and "Other" non-Hispanic, and refer to the first three categories as White, Black, and Latinx (Latino or Latina). We do not display Other in results due to insufficient sample size and substantial heterogeneity in the group. We use information on the place of birth to distinguish "Latinx, US-born" from "Latinx, non-US-born". Educational attainment is divided into three categories: less than a high school diploma (henceforth, less than high school-LTHS), high school diploma/general equivalency degree/some college (HS/GED), and Associate degree or higher (A/BA+).

3.3 Analytic strategy

We use predicted probabilities from discrete-time (logit) survival models in conjunction with discrete-time Markovian multistate life table techniques (Millimet et al. 2003; Schneider 2023)[6] in order to calculate life expectancies for the different subgroups. This necessitates an analytic chain that consists of three steps. First, logistic regressions model the probability of dying as

$$(1) \qquad \log\left(\frac{p}{1-p}\right) = a + b_1\, Age + \; b_2\, Age^2 + \boldsymbol{\gamma} \cdot DEMOGR\_INTERACT,$$

where p is the probability of dying. The right-hand side includes the intercept, a linear and quadratic term for age, and a full set of interactions of race/ethnicity (including nativity for Latinx) with education (DEMOGR_INTERACT). The sample is split by gender.

Second, we use the estimated regression models to predict probabilities of dying for the age range 50-110. This is done separately for the subpopulations implied by the combinations of gender, race/ethnicity, and education, and (in section 4.3) childhood adversities. For such predictions, probabilities are calculated by setting categorical indicators to either 0 or 1, corresponding to a specific population subgroup (e.g., "Black women with an Associate degree or higher").

Finally, in the third analytical step we use multistate Markov chain modeling techniques to calculate life expectancy at the baseline age of 50 years. While our mortality application is not a multistate one, it can be seen as being contained in (and being the simplest case of) a multistate setup. We adopt this perspective since recent developments in discrete-time multistate modelling conveniently allow us to calculate life expectancies and their (asymptotic) standard errors, as well as to make group comparisons (Schneider 2023).

3.3.1 Analyses including childhood adversities

We first analyze the interactions of gender, race/ethnicity and education, and in Section 4.3 we add childhood adversities. Our baseline measure is a cumulative count of up to seven distinct childhood (under age 16) circumstances (coded yes=1, no=0, unless otherwise noted). Similar indices are used in Montez and Hayward (2014) and Lorenti et al. (2020). The individual components are numbered 1 to 7: 1) whether the respondent's father had a blue-collar job[7], 2) whether the respondent's father was unemployed, absent, or deceased, 3) whether the parents had low education (average fewer than 8 years=1, otherwise=0), 4) self-rated family financial situation before age 16 (poor=1, average/pretty well off=0), 5) whether the respondent's family ever moved because of financial difficulty, 6) whether the respondent's family ever received financial help from relatives, and 7) self-rated health, (poor/fair=1, good/very good/excellent=0). Data for all waves relevant for the estimation sample 1998-2018 are taken from HRS core files.

We construct several different measures from this baseline: a cumulative count of the above seven components divided into categories 0, 1-4, 5+; a cumulative count divided into categories 0-1, 2-3, 4+, as in Lorenti (2020); a cumulative count divided into two categories only, 0-1 vs. 2+; a cumulative count used as a quasi-continuous linear measure; and a 3-category measure that simultaneously lends higher importance to childhood health (Montez and Hayward 2014) and avoids near-empty cells in the interacted variables by having a sufficient number of deaths in the lowest and highest adversity categories. Here, low adversity is defined by good childhood health and at least one of high parental education and the respondent's father having had a white-collar job. The high adversity category is defined by poor childhood health or by the respondent's father having a blue-collar job plus three other adversities. The middle category is defined by the remainder.

To avoid loss of observations due to missingness, we apply the same procedures as Lorenti et al. (2020). If information on both parents' education is missing, we set education to low; if father's occupation is missing, we set it to blue-collar if parents' education is low or if the father did not economically contribute to the family's income. After these adjustments, 8.7% of respondents still have one or more components missing, most of whom have only one component missing (5.5% of respondents). We exclude respondents that have five or more components missing, but ignore other missingness in the summations.

In the context of our four-dimensional analyses, data scarcity in some cells forced the redefinition of other regressors. The core of the problem is statistical interactions: for an analysis rooted in intersectionality and that tests theories about cumulative (dis)advantage, the research design must include interactions (or stratify) across all the relevant intersecting variables; controlling for any of the variables is not enough, as that would not inform us about intersecting dimensions of advantage or disadvantage. While data requirements depend on several parameters, a useful approximation is that in order to estimate binary interactions without losing statistical power, one needs 4 to 16 times more data than for the main effect: 4 if the interaction is of the same size as the main effect; 16 if the interaction is half the size (Gelman, Hill, and Vehtari 2020). Our sample is approximately 36,000 individuals. If we consider the interaction effect sizes to be large, this means that after gender, race/ethnicity, nativity, and education interactions, we have an effective sample size of 36,000/(4^4) ≈ 140 observations for every sub-population. Our empirical results from Section 4.2 show that such effective sample size is enough. However, adding even a binary early-life adversity variable cuts the effective sample to approximately 35.[8]

As a consequence, we must combine some of the dimensions to maintain statistical power. In our exploration of estimable specifications, we do one or more of the following: We simplify race/ethnicity by dropping "Other." We also combine US-born and foreign-born Latinx, despite being aware these populations have different health profiles; we reduce educational attainment from a 3- to a 2-category measure, combining high school degree/GED/some college and Associate+ as indicative of higher education; and we redefine the three categories of childhood adversities or collapse them into two categories.

However, even after these power-preserving maneuvers, the data is often too thin to provide conclusive evidence about the nature and direction of inequalities when childhood adversities are considered. We illustrate this lesson with a specification curve analysis that explores the results across a large number of specifications, without committing to any specific model specification (Simonsohn, Simmons, and Nelson 2020).

A replication script that includes all aspects of data construction as well as all underlying calculations for the tables and figures is available at the Open Science Framework.[9] We conduct all analyses using Stata 17.

4 Results

4.1 Descriptive characteristics

Table 1 presents the composition of the sample (1998-2018). Panel A documents that in total we have 36,226 subjects that contribute 239,053 person-waves and 13,238 deaths. The average age is 67 years, women contribute 53% of the observations. Race/ethnicity and education distributions are as expected, the majority of the sample is White (75%) and half of the sample has HS/GED education. The average number of childhood adversities in the sample is 1.9.

Panel B of Table 1 breaks the sample by race/ethnicity, gender, childhood adversities, and educational attainment. This illustrates both inequalities in childhood adversities and education as well as challenges with sample size. Among both men and women, Whites, compared with Blacks and Latinx, have a higher likelihood of reporting no childhood adversities, as well as being 2-3 times more likely to belong to the highest education group compared to the lowest (for example: among White women 13% vs. 5.5%). For all other groups, the highest adversity and lowest education categories are more prevalent than the lowest adversity and highest education, and among Latinx there are 2-8 times more individuals in the lowest-education category than the highest.

[Table 1]

4.2 Intersections among gender, race/ethnicity, nativity, and education

4.2.1 Cumulative (Dis)advantage

A substantial body of prior research shows the persistent gender, racial/ethnic, and educational disparities in life expectancy (e.g., Case and Deaton 2021; Miech et al. 2011). Therefore, instead of focusing on the main effects, we will focus on the questions of intersectionality and cumulative (dis)advantage.[10] In this section, cumulative (dis)advantage is measured in the most common way: conditional on having one disadvantage, how is an additional disadvantage associated with the outcome? What we have termed "outcome-focused." We do not yet factor in the *likelihood* of experiencing an additional (dis)advantage.

Table 2 summarizes the results in terms of cumulative (dis)advantage, focusing on the contrasts between highest and lowest education categories (the middle category is shown in Figure 1). The table shows first the life expectancy levels (Panel A; also illustrated in Figure 1); in Panel B we show educational differences in life expectancy for each of the subpopulations; and Panel C indicates when the difference points towards cumulative advantage, when towards cumulative disadvantage.[11]

High-educated women have the highest life expectancy (Table 2 Panel A). Across racial/ethnic categories, Blacks have the lowest and non-US born Latinx have the highest life expectancy among both men and women and in all education groups. Educational differences are particularly pronounced among Whites (Panel B): Among White women, the highest education level is associated with 5.6 years (17.9%) higher life expectancy than lowest, and among men the difference is 5.8 years (20.9%). For other racial/ethnic groups the differences are mostly smaller, both in absolute and relative terms. For example, among Black women and men the difference is 2.9 years, or approximately 10%.

Panel C of Table 2 converts these educational differences into insights about cumulative (dis)advantage. As noted above, educational differences are particularly pronounced among Whites. This means that Whites gain[12] more from higher education than other racial/ethnic groups. Therefore Panel C is populated with "A"s, indicating the cumulative advantage that Whites have when compared to Blacks, US-born Latinx, and non-US born Latinx. This holds throughout, for men and women, and for the relative and absolute differences. Importantly, the results do not indicate cumulative disadvantage. Consider as an example Blacks: they lose less, not more, from low education than Whites (2.9 years vs 5.6 or 5.8 years). Therefore, per our definition, the life expectancy differentials do not indicate cumulative disadvantage.

[Table 2 and Figure 1]

4.2.2 Opportunity-Weighted Cumulative (Dis)advantage

Opportunity-weighted cumulative (dis)advantage introduces into the assessment of inequalities the probability of acquiring an additional (dis)advantage. This speaks more directly to the temporal nature—the *accumulation* of (dis)advantage across the life course, such as the racial/ethnic patterning of access to educational opportunities, thus attainment. Table 3 Panel A presents the probabilities, or weights, in terms of both cumulative disadvantage, i.e., the proportion with lower education (less than high school), and cumulative advantage, the proportion with higher education (Associates or higher). It also shows the probability-weighted benefits of higher education in terms of the increase in total life expectancy. For example, White women lose 5.6 years from having low education, compared to high, and 29.4% of White women have low education. The probability weighted loss is 29.4% * 5.6 = 1.6 years. For US-born Latinx, the respective numbers are 69% and 2.6 years, resulting in probability weighted loss of 69% * 2.6 = 1.8 years. US-born Latinx thus lose more than Whites, and this is indicated by the D (opportunity-weighted cumulative disadvantage) in Panel B of Table 3.

Similar comparisons for other racial/ethnic groups and for men and women suggest predominantly that when the low likelihood of high education is taken into account, Blacks, US born Latinx, and non-US born Latinx experience cumulative disadvantage compared to Whites. The pattern is not uniform, however. For example, even though the vast majority of non-US born Latinas have low education (83.2%), life expectancy differences between high- and low education within this sub-population are so small (1.1 years) that the probability-weighted loss is less than among Whites. Therefore, per our definition, they do not experience opportunity-weighted cumulative disadvantage compared to Whites. The reasoning is similar for Black women who also have a smaller loss from low education than White women.

The right-hand side of Panels A and B of Table 3 describe opportunity-weighted cumulative advantage. These results uniformly show that if we account for the much higher likelihood of acquiring the additional advantage – high education – among Whites, cumulative advantage always results.

[Table 3]

4.3 Considering the long arm of childhood

Thus far, we have focused on the intersections of gender, race/ethnicity, nativity for Latinx individuals, and educational attainment. However, the accumulation of (dis)advantages across the life course includes the impact of early life, as much research on the "long arm of childhood" shows (Ferraro et al. 2016; Hayward and Gorman 2004; Schafer, Ferraro, and Mustillo 2011). As detailed in the Data and Methods section, we were forced to change our approach in order to try and incorporate this fifth element of childhood adversity. We simplified our race/ethnicity and education measures. Nevertheless, the challenges of considering five complex elements in our analysis proved to be insurmountable, and so below we present a set of analyses that explores results across a number of specifications.

We present ten specifications (I)-(X) for estimating the four-dimensional interactions that include childhood adversities. All models use a measure that is based on a cumulative count of adverse childhood experiences and a full four-way interaction of gender-education-race/ethnicity/nativity-childhood adversity, where the interaction by gender is implicit for the first eight models where samples are split by gender.

The baseline model (I) corresponds to the model described in section 3.3, with an expanded interaction (DEMOGR_INTERACT in equation (1)) that now additionally contains a 3-category measure of childhood adversities. Models (II)-(X) are modified versions of model (I) and can be seen as progressing to ever more parsimonious specifications. This is achieved by one or more of the following: A) The 3-category variables measuring childhood adversities uses different adversity count categories with a more even distribution of occurrence (models II-IV, VI), or is reduced to two categories only (models VII-X), or childhood adversities enter as a quasi-continuous variable (model V); B) The 4-category variable on race/ethnicity/nativity is now race/ethnicity only, i.e., the distinction between US-born and non-US-born Latinx is no longer made (model IV) ; C) The 3-category variable measuring education is reduced to two categories (models VI, VIII, XI) or changed to an entirely different 2-category measure (parents' education, which is predictive of other adversities; model X); D) Gender is no longer used as a criterion for a sample split but included as a regressor in the interaction (models IX, X). In addition, the "Other" category of the race/ethnicity/nativity variable, which was previously included but not shown in results, is now excluded from the estimation sample for all models. The individual model specifications are listed one-by-one in the figure notes of Figures 2 and 3.

[Figure 2]

[Figure 3]

Figure 2 (women) and 3 (men) present estimates of total life expectancy for only the lowest and highest childhood adversity categories for each of the 10 models, and Figures 4 and 5 plot the difference between high and low adversity. The top-left panel of each figure shows life expectancy (or differences) for low-educated White women. For the first adversity specification, we estimate that women who experience more early life adversity have slightly (not significantly) higher life expectancy. For the other specifications, more adversity is predictive of lower life expectancy, as expected.

This feature that for some model specifications we estimate a higher life expectancy for those who have fewer early life adversities, and for some specifications the opposite, holds across most of the subpopulations. For example, among low-educated Latinas, Model I estimates that those without early life adversity have 5 years higher life expectancy. However, most other models for the same group estimate that no early life adversity is associated with lower life expectancy. The pattern is equally inconclusive for many of the subpopulations. For example, among Latinx, it holds for both men and women, for US-born and non-US born, and for high and low-education categories that some specifications suggest that early life adversity is associated with lower life expectancy, and other models suggest the opposite.

[Figure 4]

[Figure 5]

In cases in which the results are consistently to one or the other direction, other challenges to interpretation emerge. For example: Among White women and men, early life adversity is in almost all specifications associated with lower life expectancy. However, the contrasts are rarely statistically significant. For Blacks for whom the pattern is predominantly to one direction, the direction itself is surprising, suggesting higher life expectancy for those with high early life adversity (for example, Figure 5, low educated Black men). However, none of these contrasts is statistically significant.

This specification curve analysis shows that whether early life adversity is associated with better or worse life expectancy at older ages, and among whom, is strongly dependent on model specification. We carefully examined all 10 models shown here. We were not able to make a theoretical argument as to why one or some of the models should have priority in the interpretation of the results. Further, each model in itself produced results that, even if they appeared to be credible for some sub-population, were surprising for some other sub-population. We were humbled by this exercise and conclude that the HRS, which is arguably the best suited large-scale data for analyzing how various dimensions of advantage and disadvantage produce inequities in old-age health, is not powerful enough to produce conclusive results about early life adversity in combination with other key measures of (dis)advantage.

5 Discussion

5.1 Our task

We argue that despite repeated attempts to lay out the theories of intersectionality and cumulative (dis)advantage more clearly, they continue to be used rather too loosely in the literature. To offer a clear foundation for our own analysis, we start by historicizing intersectionality and distinguishing between what we term "outcome-focused" (the traditional) and "opportunity-weighted" cumulative (dis)advantage. By outcome-focused cumulative (dis)advantage, we mean the approach wherein we ask the question: among those who have one disadvantage (e.g., Black v. White), how does having an additional disadvantage (e.g., low education v. high) affect an outcome compared with those who do not have the first disadvantage? This analysis, following the approach traditionally used in the literature, focuses on the outcomes, overlooking the likelihood of attaining the (dis)advantages, and conditions on individuals being positioned on two axes of (dis)advantage. We work through a mathematical proof demonstrating that cumulative advantage and disadvantage are mutually exclusive whether measured on an absolute or relative scale. Our proof demonstrates that Blacks either lose more from lower education (cumulative disadvantage) or Whites gain more from high education (cumulative advantage). They are mutually exclusive.

We next put forward a novel concept that we call "opportunity-weighted cumulative (dis)advantage" that incorporates the probability of a (dis)advantaged group acquiring another (dis)advantage. This measure is intended to reflect more explicitly the temporal component, acknowledging that, due to opportunity structures, (dis)advantages tend to accumulate across a life course, as in the original articulation of "the Matthew effect": the rich get richer and the poor, poorer (Merton 1968, 1995).

In the first section of our analysis (Section 4.2), we study how the intersections of gender, race/ethnicity, nativity for Latinx, and educational attainment are associated with life expectancy at age 50. Our estimates take into consideration not just whether those with multiple disadvantages have worse health outcomes than would be expected based on the intersection of their individual disadvantages (Table 2), but also the probability of acquiring additional (dis)advantages (Table 3).

In the second part of our analysis (Section 4.3), we include childhood adversities. Data constraints lead us to present, instead of conclusive results, a specification curve analysis of total life expectancy (TLE) using four different operationalizations of childhood adversity and ten model specifications. These analyses demonstrate the wild variability in TLE estimates even when based on substantially simplified models (Figures 2-5).

With two scales (absolute and relative), five sociodemographic risk factors (gender, race/ethnicity, nativity for Latinx, childhood adversity, and educational attainment), as well as an outcome-focused and opportunity-weighted approach to measuring cumulative (dis)advantage, we have presented quite a number of results. We only have capacity to interpret some of the results herein, but we present all results either in the text, tables, figures, or in appendices.

5.2 Interpretation

To summarize, all evidence points toward the importance of applying an intersectional lens in studying life expectancy in that the width, and sometimes even direction of, inequities depend on the intersections of these axes of privilege. Nevertheless, we find that White women and men experience cumulative advantage across all metrics and regardless of absolute or relative scale measurement (i.e., compared to Blacks or Latinx, Whites gain more from high education than the other groups). This holds also independently of whether we factor in the differential likelihood of attaining higher education.

Cumulative disadvantage, on the other hand, is not supported by the data as uniformly as cumulative advantage. First, as we show in the paper, under the traditional, outcome-focused definition of cumulative (dis)advantage, existence of cumulative advantage means that cumulative disadvantage does not exist. We have found, throughout the comparisons, that Whites gain more from high education than Blacks or Latinx groups. Therefore, Blacks and Latinx lose less from low education, compared to Whites, and only cumulative advantage, but not cumulative disadvantage, describe the inequalities. While at first blush that might seem counterintuitive, the implications of this are in line with other research, for example, that higher educational attainment does not insulate Blacks from health insults (e.g., Geronimus 1992).

However, when we factor in the differential likelihood of attaining low versus high education, evidence for cumulative disadvantage emerges. Blacks and Latinx have a higher likelihood of only attaining a low level of education than whites, and when this is taken into account, the opportunity-weighted cumulative disadvantage metric shows that for most comparisons, Blacks and Latinx experience cumulative disadvantage compared to Whites.

5.3 Limitations

There are at least two key weaknesses in this study. First, even though we analyze multiple dimensions of (dis)advantage, and therefore acknowledge heterogeneity within populations, our analysis is not able to account for the inherent heterogeneity within *sub*-populations. For example, the likelihood of high education may not be high for all Whites, and the loss from low education – conditional on having low education – may not be high for all Blacks. Incorporating sub-population heterogeneity into the analysis of cumulative (dis)advantage would be an important next step and should be done both on the formal level of definitions and at the level of empirical analysis. This is beyond the scope of the current paper.

Second, our analysis of early life adversity and its relation to other dimensions of (dis)advantage was severely limited by statistical power. Instead of being able to illustrate what early life adversity means across sub-populations, we were only able to demonstrate the limits of what can be known: not much. Statistical analysis using arguably the best possible data for this purpose was underpowered to detect robust associations. We consider this both a limitation and an important finding in itself and interpret the ambiguity in the results as a call for larger-scale data collection particularly for disadvantaged sub-populations.

6 Conclusions

Despite the limitations, this analysis builds on previous work in several important ways. First, we offer clear definitions of both the traditional concept of cumulative (dis)advantage and a novel approach – opportunity-weighted cumulative (dis)advantage, including working through mathematical proofs that illustrate their characteristics and alternative measurement scales—both absolute and relative. Second, we focus on studying how intersections of gender, race/ethnicity, nativity for Latinx, and educational attainment pattern life expectancy. Third, we incorporate a measure of childhood adversity and present a range of results related to the operationalization of that adversity. This demonstrates the importance of transparency.

Grounded in theories of intersectionality and cumulative (dis)advantage, we develop complementary formalizations of (dis)advantage to study inequities in life expectancy: *Cumulative (Dis)advantage* that reflects inequities in outcomes, and *Opportunity-Weighted Cumulative (Dis)sdvantage* that additionally accounts for inequities in opportunities. Using these formalizations, we empirically illustrate dramatic disparities that show how the benefits and penalties of one (dis)advantage depend on positionality on the other axes of inequality. Using the *outcome-focused* definition, Whites ubiquitously experience c*umulative advantage*: they benefit more from higher education than Blacks or Latinx. However, when accounting for inequalities in educational attainment, results predominantly show *opportunity-weighted* c*umulative disadvantage* for Black and Latinx men and women compared with Whites. Our formalization provides a mathematical grounding for cumulative (dis)advantage analysis, and the empirical results comprehensively document the multi-dimensional, intersecting axes of stratification that perpetuate health inequities.

Notes

1. Extensions to more than two categories are possible. For the traditional approach, additional dimensions can be included as long as one conditions on these dimensions. For the opportunity-weighted approach, additional dimensions require taking the expectation over these additional dimensions.
2. The formal steps are: $(\mathrm{B}-\mathrm{A}) > (\mathrm{D}-\mathrm{C}) \Leftrightarrow (\mathrm{B}+\mathrm{C}-\mathrm{A}) > \mathrm{D} \Leftrightarrow (\mathrm{C}-\mathrm{A}) > (\mathrm{D}-\mathrm{B})$
3. We assume no strict equality, that is no B-A = D-C. If the outcome is categorical, strict equality may occur. Then the data supports neither of the definitions, neither traditional cumulative advantage nor disadvantage. In the case of a continuous outcome, strict equality has zero probability of occurring, so the point estimates support either advantage or disadvantage.
4. The formal steps are: $\frac{\mathrm{B}-\mathrm{A}}{\mathrm{B}} > \frac{\mathrm{D}-\mathrm{C}}{\mathrm{D}} \Leftrightarrow \left(1-\frac{\mathrm{A}}{\mathrm{B}}\right) > \left(1-\frac{\mathrm{C}}{\mathrm{D}}\right) \Leftrightarrow -\frac{\mathrm{A}}{\mathrm{B}} > -\frac{\mathrm{C}}{\mathrm{D}} \Leftrightarrow \frac{\mathrm{B}}{\mathrm{A}} > \frac{C}{D}$
5. Notwithstanding some (still contentious) evidence of the accumulation of (dis)advantage causing racial fluidity (Alba, Lindeman, and Insolera 2016; Saperstein and Penner 2012).
6. See Millimet et al. (2003) for an early application and the appendix of Schneider et al. (2023) for a methodological introduction.
7. If information on father's occupation was missing, the blue-collar indicator was set to true if either adversity 2) (father absent/unemployed/deceased) or 3) (parents had low education) was true. This was the case for 2,819 individuals.
8. This calculation cuts corners. The effective sample size is on the one hand larger as the data is longitudinal; on the other hand, it is smaller since some interactions are multi-category (education). Such detail is not critical for the argument that the data just gets too thin when childhood characteristics are included.
9. https://osf.io/y8dnz/?view_only=1d31f2f3b56042c3b3ca13356904f800
10. With 24 intersections (4 race/ethnicity/nativity, 2 gender, 3 education levels), disparities among those intersections, the number of potential comparisons is large. Readers who would like to focus on main effects and/or other intersectional disparities can use the figures and tables in the main text and appendices to glean further information.
11. The numbers for the relative percentage change shown in the table are the ones relevant for the condition of CA (or CD) on the relative scale, minus one. The condition remains unchanged, of course. For CA, we have D/C>B/A <=> D/C-1>B/A-1 <=> (D-C)/C>(B-A)/A. The

denominator used corresponds to the values for low education. One could have equivalently divided the differences by the high-education numbers: D/C>B/A <=> C/D <A/B <=> (D-(D-C))/D<(B-(B-A))/B <=> 1-(D-C)/D<1-(B-A)/B <=> -(D-C)/D<-(B-A)/B <=> (D-C)/D>(B-A)/B. That is, it does not matter whether the high-education or the low-education values are used in the denominators when dividing the absolute differences. An analogous argument holds for the condition of CD.

12. It is important to note we are not making a causal argument; however, for simplicity, we use the expressions such as “gain” or “benefit” to mean that higher education is associated with longer life expectancy.

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Boxes, Tables, and Figures

Box 1: Traditional Definition of Cumulative Advantage and Disadvantage

	Levels of the outcome		**Educational changes in the outcome**	
Race/Ethnicity	Low education	High education	Absolute scale	Relative scale
Black	A	B	B-A	B/A
White	C	D	D-C	D/C

Assumptions (for a positive outcome, e.g., life expectancy; higher values are beneficial):

A<C, B<D : within education levels, Blacks have lower levels of the beneficial outcome

A<B, C<D : within race/ethnicity, higher education leads to higher levels of the beneficial outcome

Decision rules

Absolute scale:

Cumulative disadvantage: B-A > D-C (Blacks lose more from low education)

Cumulative advantage: B-A < D-C (Whites gain more from high education)

Relative scale:

Cumulative disadvantage: B/A > D/C (Blacks lose proportionally more from low education)

Cumulative advantage: B/A < D/C (Whites gain proportionally more from high education)

Mathematical implications:

Traditional absolute disadvantage implies traditional relative disadvantage, but not vice versa.

Traditional relative advantage implies traditional absolute advantage, but not vice versa.

Box 2: Opportunity-Weighted Definition of Cumulative Advantage and Disadvantage

	Outcome levels		**Population fractions**				**Opportunity-weighted changes in outcome**	
Race / Ethnicity	Education		Raw		Probabilities within race/ethn.		Loss from low educ	Gain from high educ
	Low	High	Low	High	Low educ.	High educ.		
Black	A	B	a	b	P_A=a/(a+b)	P_B=b/(a+b)=1-P_A	P_A * (B-A)	P_B * (B-A)
White	C	D	c	d	P_C=c/(c+d)	P_D=d/(c+d)=1-P_C	P_C * (D-C)	P_D * (D-C)

Assumptions: as under Box 1

Decision rules:

Cumulative disadvantage: P_A*(B-A) > P_C*(D-C) (Blacks lose more from low education)

Cumulative advantage: P_B*(B-A) < P_D*(D-C) (Whites gain more from high education)

Mathematical implications: none

Table 1: Descriptive characteristics of our analytical sample from the Health and Retirement Study (1998-2018)

Panel A

Person-Waves, total	239,053
of which: deaths	13,238
Number of individuals	36,226
Age (years, mean)	67.3
Gender, %	
Men	47.1
Women	52.9
Race/Ethnicity, %	
White	75.0
Black	11.3
Latinx	9.0
Latinx, US-born	3.7
Latinx, non-US-born	5.3
Childhood adversities (0-7), mean	1.9
Educational Attainment, %	
Less than High School	17.6
HS/GED/Some College	51.0
Associate+	31.4

Panel B

	Race/Ethnicity				
				Latinx US-born	
Gender and Educational Attainment	All race/ ethnicity	White	Black	Yes	No
Women	53.1	41.6	6.6	2.0	2.9
Childhood adversity (mean)	1.9	1.9	2.1	2.1	2.1
0	8.7	8.0	0.4	0.1	0.2
1-4	40.7	31.2	5.5	1.6	2.3
5-7	3.7	2.3	0.7	0.3	0.4
Education					
Less than High School	9.6	5.5	1.8	0.7	1.6
HS/GED/Some College	28.2	23.0	3.2	1.0	0.9
Associate+	15.3	13.1	1.5	0.3	0.3
Men	45.7	37.5	4.4	1.7	2.1
Childhood adversity (mean)	1.9	1.9	2.0	2.1	2.1
0	7.9	7.3	0.3	0.1	0.2
1-4	35.9	27.9	4.4	1.4	2.2
5-7	3.1	1.9	0.6	0.3	0.3
Education					
Less than High School	7.7	4.5	1.4	0.6	1.2
HS/GED/Some College	22.5	18.9	2.2	0.8	0.6
Associate+	15.6	14.2	0.8	0.3	0.3

Notes: Panel A: Characteristics of the full sample; panel B: Sample Means or Percentages by Gender, Educational Attainment, Race/Ethnicity, and nativity. HS is High School; GED is general equivalency degree. All calculations are based on survey weights. Survey nonresponses are counted as part of the sample as long as the mortality status had been ascertained.

Table 2: Traditional cumulative (dis)advantage

Panel A: Raw outcomes (life expectancy)

	Less than high school				Associate+			
			Latinx				Latinx	
	White	Black	US-born	non-US-born	White	Black	US-born	non-US-born
Women	31.2	30.1	33.4	35.9	36.8	32.9	36.0	37.0
Men	27.9	26.4	26.9	33.4	33.8	29.3	31.9	37.6

Panel B: Educational differences in outcomes, absolute and relative scales

	Absolute (difference, years)				Relative (% change)			
			Latinx				Latinx	
	White	Black	US-born	non-US-born	White	Black	US-born	non-US-born
Women	5.6	2.9	2.6	1.1	17.9	9.5	7.8	3.0
Men	5.8	2.9	5.0	4.2	20.9	11.2	18.7	12.5

Panel C: Cumulative advantage or disadvantage

	Absolute				Relative			
			Latinx				Latinx	
	White (ref.)	Black	US-born	non-US-born	White (ref.)	Black	US-born	non-US-born
Women	.	A	A	A	.	A	A	A
Men	.	A	A	A	.	A	A	A

Notes: Panel A shows life expectancy values by gender, education level, race/ethnicity, and nativity. Panel B calculates the educational gradient (higher education outcome minus lower education outcome) in both absolute and relative terms. Panel C indicates whether the evidence in Panel B implies cumulative advantage (A) for Whites or cumulative disadvantage (D) for Blacks or Latinx, by nativity.

Table 3: Opportunity-weighted cumulative (dis)advantage

Panel A: Weighted (absolute) changes in outcomes

	Less than high school				Associate+			
			Latinx				Latinx	
	White	Black	US-born	non-US-born	White	Black	US-born	non-US-born
Women								
Population weight	29.4	53.7	69.0	83.2	70.6	46.3	31.0	16.8
Change in outcome	1.6	1.5	1.8	0.9	4.0	1.3	0.8	0.2
Men								
Population weight	25.4	58.8	63.0	81.8	74.6	41.2	37.0	18.2
Change in outcome	1.5	1.7	3.2	3.4	4.3	1.2	1.9	0.8

Panel B: Opportunity-weighted cumulative advantage or disadvantage

	Cumulative disadvantage				Cumulative advantage			
			Latinx				Latinx	
	White (ref.)	Black	US-born	non-US-born	White (ref.)	Black	US-born	non-US-born
Women	.	.	D	.	.	A	A	A
Men	.	D	D	D	.	A	A	A

Notes: Panel A shows the probability-weighted benefit of higher education (higher education outcome minus lower education outcome) in years of life expectancy. Panel B indicates whether the evidence in Panel A implies opportunity-weighted cumulative advantage (A) for Whites or opportunity-weighted cumulative disadvantage (D) for Blacks or Latinx, by nativity.

Figure 1: Total life expectancy at age 50 by gender, race/ethnicity, nativity, and education.

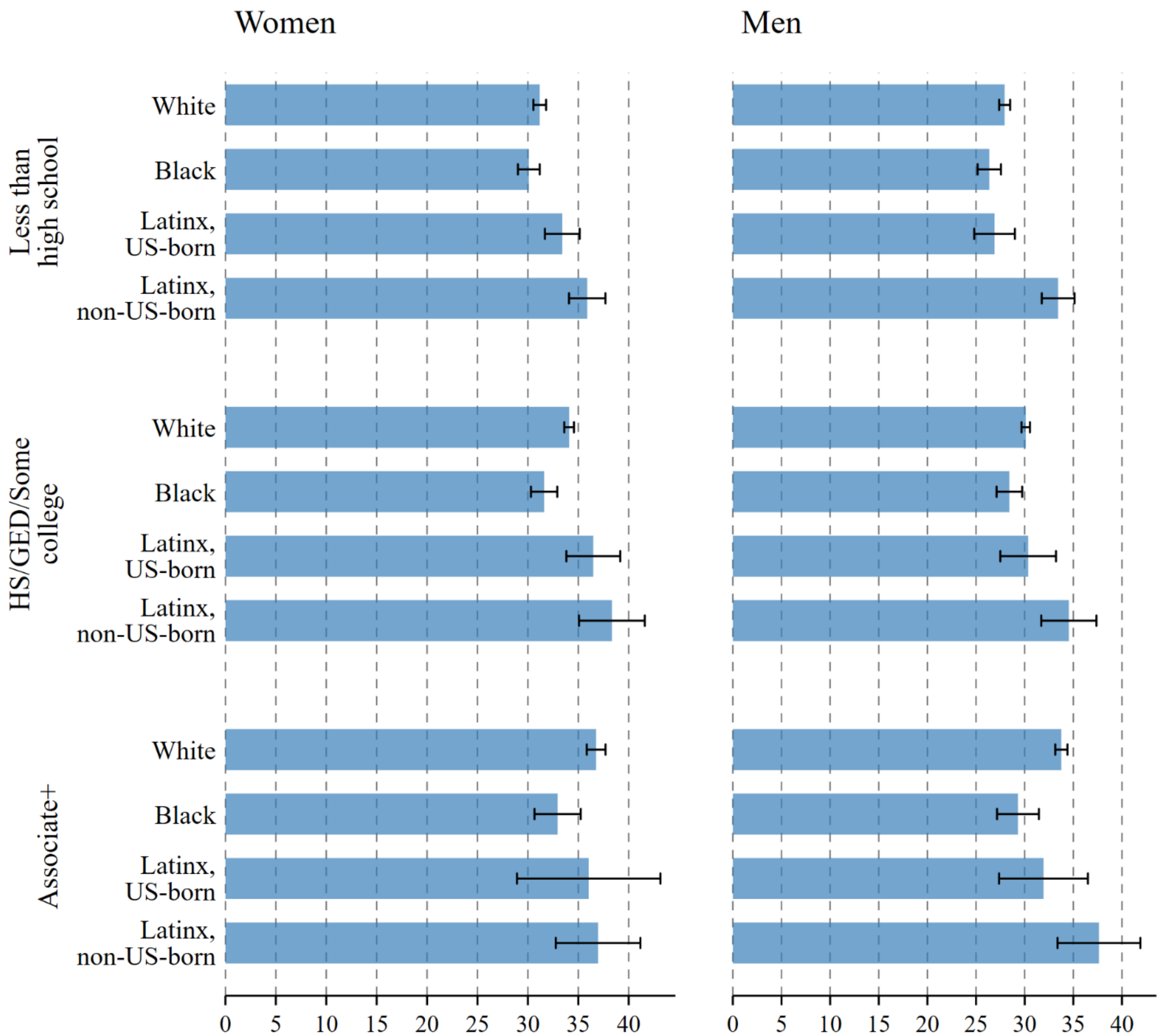
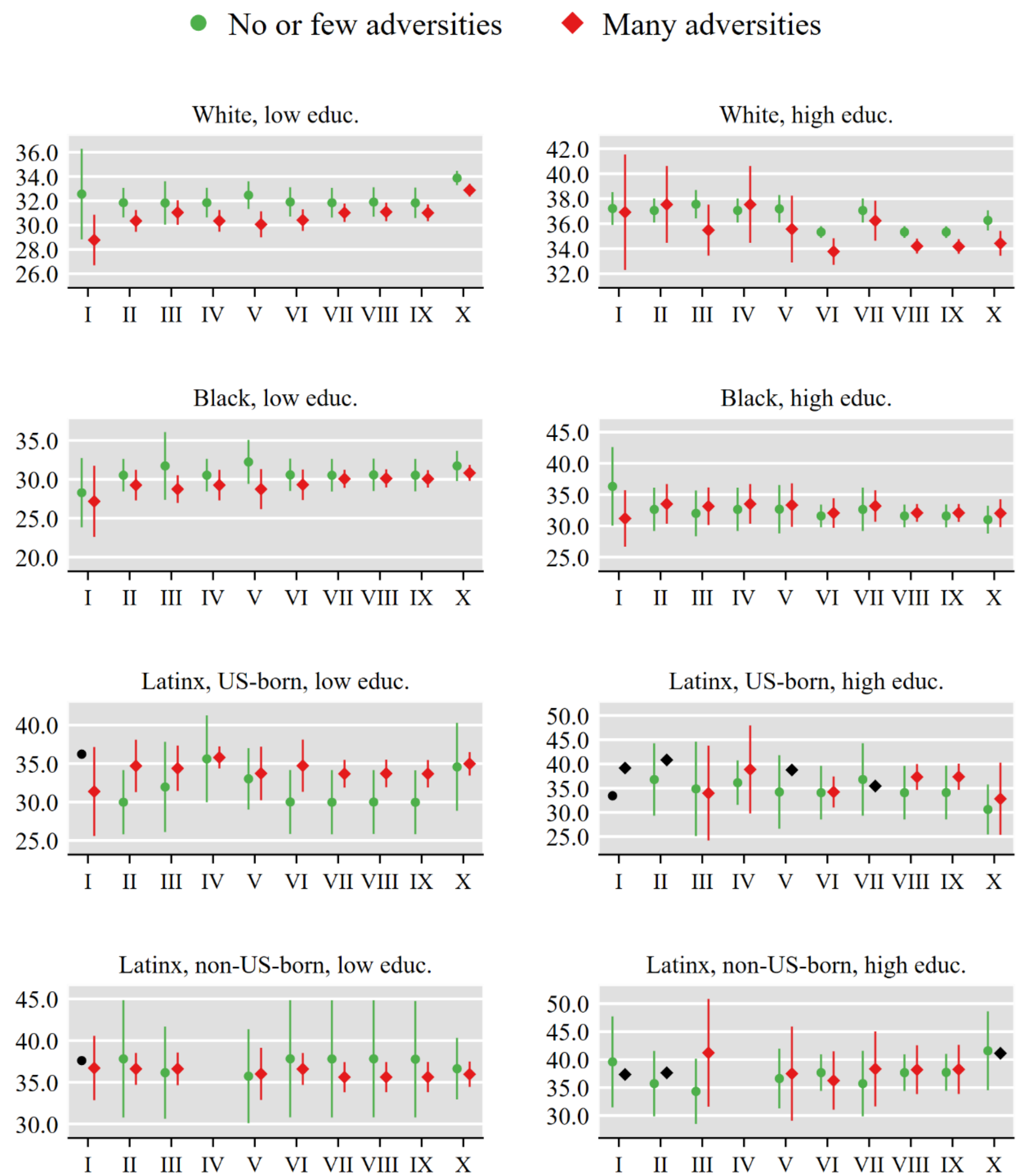
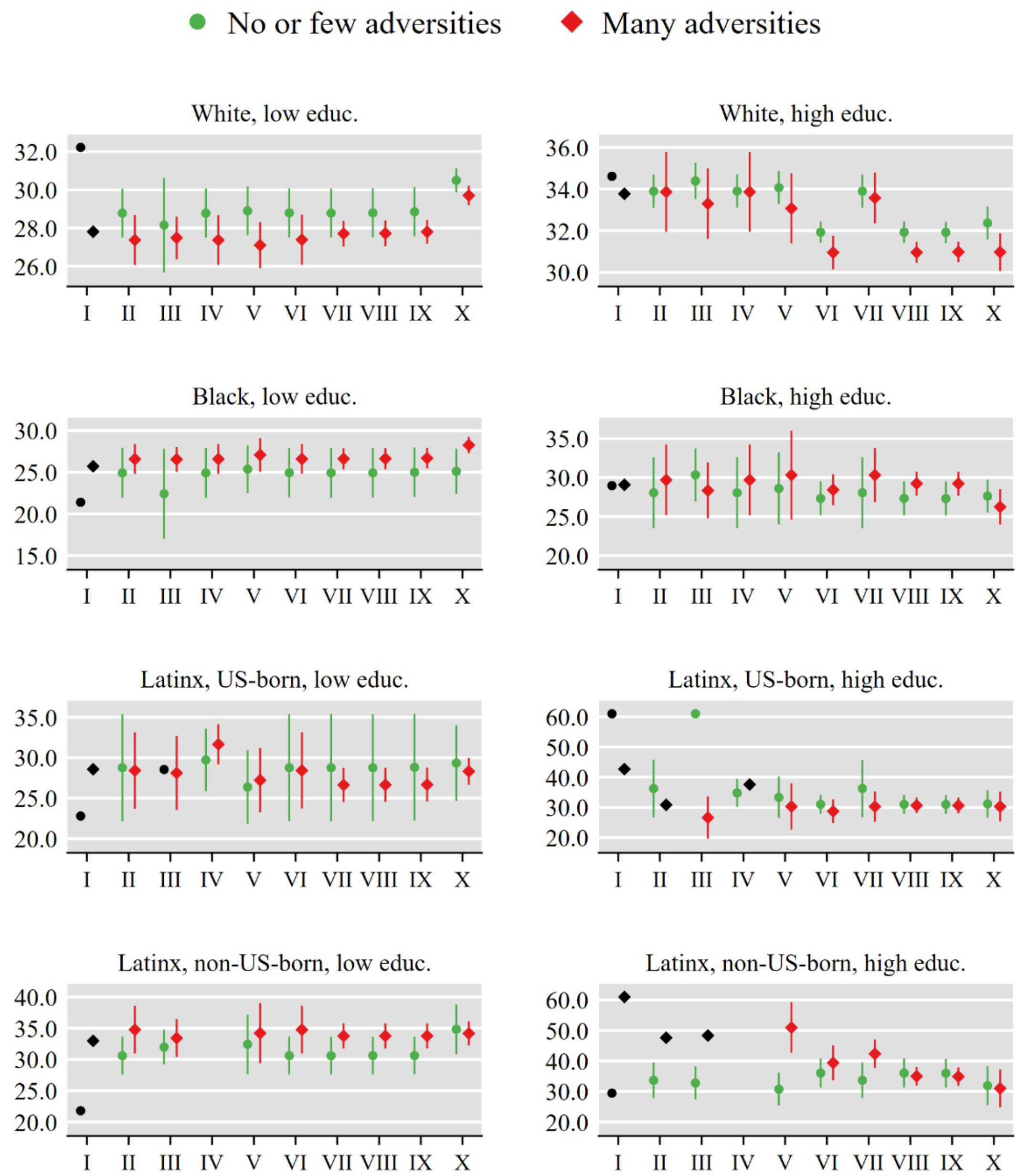


Figure 2: Life expectancy for women across various regression specifications that account for childhood adversities



Notes: Discrete-time (logit) survival models (I)-(X) that contain full interactions among education, race/ethnicity, and childhood adversities. In addition, estimates are either based on a sample split by gender or a full interaction with gender is included. Age is always included as a quadratic. Confidence intervals (CIs) are asymptotic and at the 95% level. Black markers are used for results whose CIs are very wide and therefore omitted from the figure. The baseline model (I) has the same categories as the main model in section 4.2 with respect to education, race/ethnicity, and nativity. It additionally contains childhood adversities as a cumulative count categorized into bins of 0, 1-4, and 5 or more adversities. Subsequent specifications are progressively more parsimonious. Models (II)-(X) relate to the baseline specification (I) as follows (note continued under Figure 3):

Figure 3: Life expectancy for men across various regression specifications that account for childhood adversities



(Note continued from Figure 2): Models (II)-(X) relate to the baseline specification (I) as follows:

(II) : as (I), but adversities are categorized as 0-1, 2-3, or 4+

(III) : as (I), but adversities are constructed such that a higher number of observations are in the tails (categories few, some, and many adversities)

(IV) : as (II), but US-born and non-US-born Latinx are combined in a single category (shown under US-born)

(V) : as (II), but adversities are included as a quasi-continuous variable, with predictions at 0 and 5 adversities

(VI) : as (II), but with two educational categories only (less than high school, high school or higher)

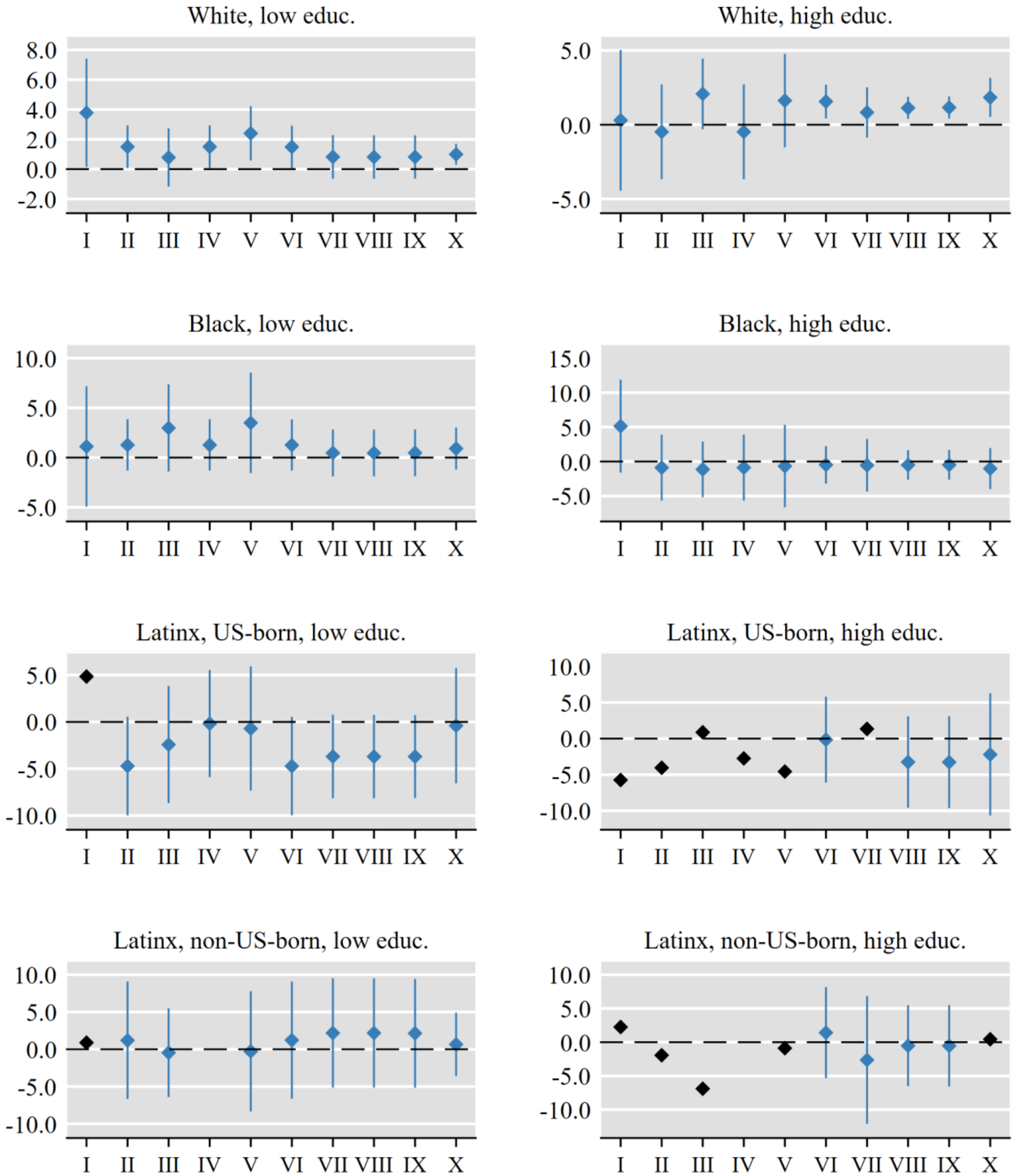
(VII) : as (II), but with two adversities categories only (0-1, 2+)

(VIII) : as (II), but with only two levels of education and adversities (according to specifications (VI and VII))

(IX) : as (VIII), but gender is included as a full interaction rather than as a sample split criterion

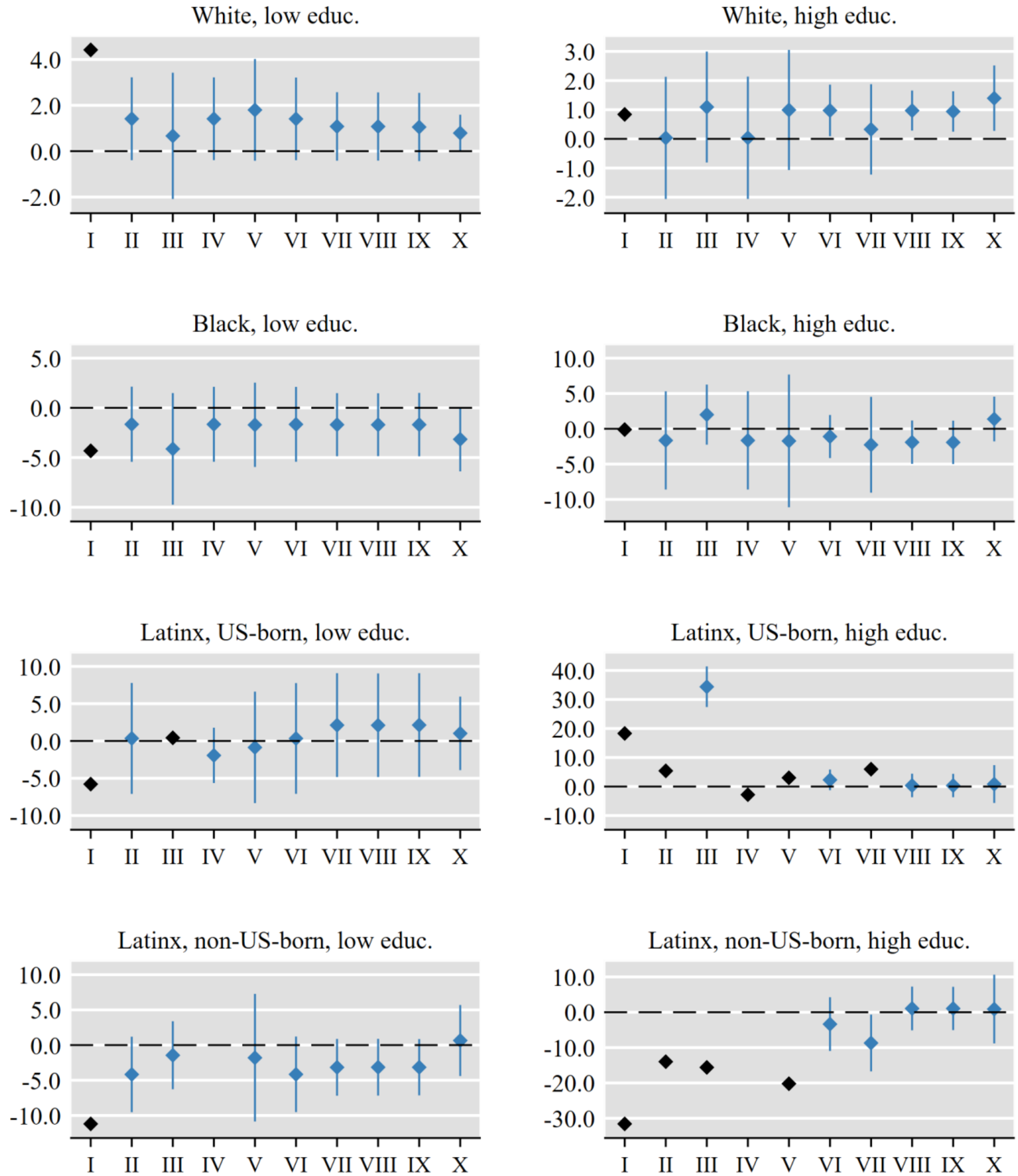
(X) : as (IX), but education is measured as binary parents' education (less than 10 years, 10 years or more)

Figure 4: Differences in life expectancy for women across various regression specifications, contrasting many v. few childhood adversities.



Notes: The labels of the horizontal axis (I)-(X) refer to the ten different regression specifications that are described in the notes of Figures 2 and 3.

Figure 5: Differences in life expectancy for men across various regression specifications, contrasting many v. few childhood adversities.



Notes: The labels of the horizontal axis (I)-(X) refer to the ten different regression specifications that are described in the notes of Figures 2 and 3.

Table A1: Traditional and opportunity-weighted cumulative advantage or disadvantage comparing low and high educated and White (ref.) and Black.

Life expectancy point estimates and 95% CIs

	White				Black			
	Less than high school		Associate+		Less than high school		Associate+	
	LE	95% CI	LE	95% CI	LE	95% CI	LE	95% CI
Women	31.2	[30.5 - 31.8]	36.8	[35.8 - 37.7]	30.1	[29.0 - 31.2]	32.9	[30.7 - 35.2]
Men	27.9	[27.4 - 28.5]	33.8	[33.1 - 34.4]	26.4	[25.2 - 27.6]	29.3	[27.2 - 31.5]

Traditional cumulative advantage

	Educational gain					
	White		Black		Difference	
	LE diff.	95% CI	LE diff.	95% CI	LE diff.	95% CI
Absolute scale						
Women	5.6***	[4.5 - 6.7]	2.9**	[0.4 - 5.3]	2.7**	[0.1 - 5.4]
Men	5.8***	[5.0 - 6.7]	2.9**	[0.3 - 5.6]	2.9**	[0.2 - 5.5]
Relative scale (%)						
Women	17.9***	[14.2 - 21.7]	9.5**	[1.2 - 17.8]	8.5*	[-0.4 - 17.3]
Men	20.9***	[17.6 - 24.1]	11.2**	[0.9 - 21.5]	9.7*	[-0.7 - 20.0]

Life expectancy

	Educational gain	
	White	Black
	LE diff.	LE diff.
Absolute Scale		
Women	5.6***	2.9**
Men	5.8***	2.9**

Opportunity-weighted cumulative advantage and disadvantage

	Pop. weight		Weighted educational gain					
	White	Black	White		Black		Difference	
	%	%	LE	95% CI	LE	95% CI	LE	95% CI
Cum. advantage(high educ. weight)								
Women	70.63	46.29	4.0***	[3.2 - 4.7]	1.3**	[0.2 - 2.5]	2.6***	[1.3 - 4.0]
Men	74.58	41.19	4.3***	[3.7 - 5.0]	1.2**	[0.1 - 2.3]	3.1***	[2.0 - 4.3]
Cum. Disadvantage (low educ. weight)								
Women	29.37	53.71	1.6***	[1.3 - 2.0]	1.5**	[0.2 - 2.9]	0.1	[-1.2 - 1.5]
Men	25.42	58.81	1.5***	[1.3 - 1.7]	1.7**	[0.2 - 3.3]	-0.3	[-1.8 - 1.3]

Table A2: Traditional and opportunity-weighted cumulative advantage or disadvantage comparing low and high educated and White (ref.) and US-born Latinx.

Life expectancy point estimates and 95% CIs

	White				Black			
	Less than high school		Associate+		Less than high school		Associate+	
	LE	95% CI	LE	95% CI	LE	95% CI	LE	95% CI
Women	31.2	[30.5 - 31.8]	36.8	[35.8 - 37.7]	33.4	[31.7 - 35.1]	36.0	[28.9 - 43.1]
Men	27.9	[27.4 - 28.5]	33.8	[33.1 - 34.4]	26.9	[24.8 - 29.0]	31.9	[27.4 - 36.5]

Traditional cumulative advantage

	Educational gain					
	White		Black		Difference	
	LE diff.	95% CI	LE diff.	95% CI	LE diff.	95% CI
Absolute scale						
Women	5.6***	[4.5 - 6.7]	2.6	[-4.3 - 9.6]	3.0	[-4.2 - 10.1]
Men	5.8***	[5.0 - 6.7]	5.0*	[-0.1 - 10.1]	0.8	[-4.2 - 5.8]
Relative scale (%)						
Women	17.9***	[14.2 - 21.7]	7.8	[-13.0 - 28.7]	10.1	[-11.5 - 31.7]
Men	20.9***	[17.6 - 24.1]	18.7*	[-0.9 - 38.3]	2.2	[-17.2 - 21.5]

Life expectancy

	Educational gain	
	White	Black
	LE diff.	LE diff.
Absolute scale		
Women	5.6***	2.6
Men	5.8***	5.0*

Opportunity-weighted cumulative advantage and disadvantage

	Pop. weight		Weighted educational gain					
	White	Black	White		Black		Difference	
	%	%	LE	95% CI	LE	95% CI	LE	95% CI
Cum. Advantage (high educ. weight)								
Women	70.63	31.00	4.0***	[3.2 - 4.7]	0.8	[-1.3 - 3.0]	3.1***	[0.8 - 5.5]
Men	74.58	37.00	4.3***	[3.7 - 5.0]	1.9*	[-0.0 - 3.7]	2.5***	[0.6 - 4.4]
Cum. Disadvantage (low educ. weight)								
Women	29.37	69.00	1.6***	[1.3 - 2.0]	1.8	[-3.0 - 6.6]	-0.2	[-5.0 - 4.7]
Men	25.42	63.00	1.5***	[1.3 - 1.7]	3.2*	[-0.0 - 6.4]	-1.7	[-4.9 - 1.5]

Table A3: Traditional and opportunity-weighted cumulative advantage or disadvantage comparing low and high educated and White (ref.) and non-US-born Latinx.

Life expectancy point estimates and 95% CIs

	White				Black			
	Less than high school		Associate+		Less than high school		Associate+	
	LE	95% CI	LE	95% CI	LE	95% CI	LE	95% CI
Women	31.2	[30.5 - 31.8]	36.8	[35.8 - 37.7]	35.9	[34.1 - 37.7]	37.0	[32.8 - 41.2]
Men	27.9	[27.4 - 28.5]	33.8	[33.1 - 34.4]	33.4	[31.8 - 35.1]	37.6	[33.4 - 41.9]

Traditional cumulative advantage

	Educational gain					
	White		Black		Difference	
	LE diff.	95% CI	LE diff.	95% CI	LE diff.	95% CI
Absolute scale						
Women	5.6***	[4.5 - 6.7]	1.1	[-3.1 - 5.3]	4.5**	[0.4 - 8.6]
Men	5.8***	[5.0 - 6.7]	4.2	[-0.9 - 9.2]	1.6	[-3.4 - 6.7]
Relative scale (%)						
Women	17.9***	[14.2 - 21.7]	3.0	[-8.7 - 14.7]	14.9**	[3.4 - 26.5]
Men	20.9***	[17.6 - 24.1]	12.5	[-2.9 - 28.0]	8.3	[-7.2 - 23.9]

Life expectancy

	Educational gain	
	White	Black
	LE diff.	LE diff.
Absolute scale		
Women	5.6***	1.1
Men	5.8***	4.2

Opportunity-weighted cumulative advantage and disadvantage

	Pop. weight		Weighted educational gain					
	White	Black	White		Black		Difference	
	%	%	LE	95% CI	LE	95% CI	LE	95% CI
Cum. Advantage (high educ. weight)								
Women	70.63	16.84	4.0***	[3.2 - 4.7]	0.2	[-0.5 - 0.9]	3.8***	[2.8 - 4.7]
Men	74.58	18.18	4.3***	[3.7 - 5.0]	0.8	[-0.2 - 1.7]	3.6***	[2.5 - 4.6]
Cum. Disadvantage (low educ. weight)								
Women	29.37	83.16	1.6***	[1.3 - 2.0]	0.9	[-2.6 - 4.4]	0.7	[-2.7 - 4.2]
Men	25.42	81.82	1.5***	[1.3 - 1.7]	3.4	[-0.7 - 7.6]	-1.9	[-6.1 - 2.2]