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# Understanding cognitive impairment in the U.S. through the lenses of intersectionality and (un)conditional cumulative (dis)advantage

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**Understanding cognitive impairment in the U.S. through the lenses of intersectionality and (un)conditional cumulative (dis)advantage**

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Abstract

Grounded in theories of intersectionality and cumulative (dis)advantage, we develop complementary formalizations of (dis)advantage to study disparities in cognitive impairment: *Conditional Cumulative (Dis)Advantage* that reflects inequalities in outcomes and *Unconditional Cumulative (Dis)Advantage* that additionally accounts for inequalities in opportunities. We study the properties of these formalizations and show that cumulative disadvantage does not imply cumulative advantage. Using these formalizations and incidence-based multistate models, we analyze the Health and Retirement Study to assess how racial/ethnic, nativity, gender, early-life adversity, and educational (dis)advantages accumulate into three important metrics for characterizing later-life cognitive impairment—lifetime risk, mean age at first impairment, and cognitive health expectancies. We find that the benefits and penalties of one (dis)advantage depend on positionality on the other axes of inequality. Black women and Latinas experience *Conditional Cumulative Disadvantage* in cognitive impairment: they are penalized more from having lower education than Whites. White men experience *Conditional Cumulative Advantage*: they benefit more from higher education than Blacks or Latinx. However, when accounting for racial/ethnic inequities in educational opportunities, results ubiquitously show *Unconditional Cumulative Disadvantage.* Our formalization provides a mathematical grounding for cumulative (dis)advantage, and the empirical results comprehensively document the multi-dimensional, intersecting axes of stratification that perpetuate inequities in cognitive impairment.

# 1 Introduction

A key 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—influences life outcomes, including health. There is a growing interest in how positionality across the life course and/or on multiple axes of stratification combine to influence health. Two prominent 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 (Dannefer 1987; Merton 1968, 1988). A main distinction 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 always 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 historicize intersectionality and cumulative (dis)advantage and formalize the concept of cumulative (dis)advantage. We further develop two complementary, theoretically-justified definitions of cumulative (dis)advantage, and apply these concepts to the study of later-life cognitive health. We present results on how race/ethnicity, nativity for Latinx, gender, childhood adversity, and educational attainment intersect to produce inequities in multiple, complementary indicators of cognitive function. Because of the profound economic and human costs of dementia, it is particularly important to understand how multiple disadvantages accumulate to affect cognitive impairment, as those with the least resources to bear it may, indeed, experience the heaviest burden.

## 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 women ("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 they employed and promoted Blacks (men) and women (White) – just not Black women; 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 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 colleague is that intersectionality as "an analytic sensibility" and no methodological tool as "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 cumulative (dis)advantage point to positionality vis-à-vis power structures structuring lives (Bourdieu 1984), but cumulative (dis)advantage is more often used to describe a *temporal* process, operating across the life course, that leads to widening disparities 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," has been 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; Ferraro and Kelley-Moore 2003; Willson, Shuey, and Elder Jr. 2007).

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. Original empirical analyses of cumulative advantage involved understanding how a person's advantages accrue across time, widening inequalities, in either a "simple" (akin to compounding interest) or "path-dependent" process (both fall under DiPrete & Eirich's "strict" definition). Using Merton's (1968) example for the latter: scientific success breeds success indirectly, through the accrual of resources that enable productivity. Other conceptualizations broaden to include status-resource interactions (DiPrete and Eirich term this the “Blau-Duncan approach”) that predict additional disadvantages will result in stronger deleterious effects from each disadvantage status relative to those who are disadvantaged along fewer dimensions. This, thus, is not a simply additive effect and is much more similar to ideas of intersectionality than the original definition of CA in the strict, Mertonian sense (Ferraro, Schafer, and Wilkinson 2016; Mehta and Preston 2016).

The literature thus includes both varying and loose definitions, leaving open a large space of alternative interpretations. Moreover, most work does not address the difference between inter and intra-group or absolute and relative (dis)advantage (Bask and Bask 2015; 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).

Therefore, in order to ensure clarity in our concepts and interpretation, we clearly define cumulative advantage and disadvantage, specifically discussing two key elements: 1) what we term “conditional” versus “unconditional” cumulative (dis)advantage, 2) measurement on absolute versus relative scales.

We first formalize the concept of cumulative (dis)advantage and illustrate the interplay among the two elements. This approach allows us to deliver definitional clarifications that are critical, as, in light of the existing literature, there may be 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, 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 (Montez and Hayward 2014). This appears to indicate that White women experience one-year greater 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 Conditional and Unconditional Cumulative (Dis)advantage*

We provide both a heuristic description of two complementary definitions of cumulative (dis)advantage, conditional and unconditional, and 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. We assume that Whites and high educated have a higher level of the "reward" than Blacks and low-educated.

Our first conceptualization of cumulative (dis)advantage is conditional and 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? In other words, do Whites gain more from high education than Blacks, conditional on both having high education? Under this conditional definition, cumulative *advantage* arises if Whites gain more from high education than Blacks; cumulative *disadvantage* arises if Blacks lose more from low education than Whites.

Insight number one and the key feature of the conditional definition is that cumulative advantage is the antithesis of cumulative disadvantage: evidence for one is evidence contra the other. Whites either 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).

The conditional definition does not use information on the likelihood of attaining high education, but conditions on it. In reality, educational opportunities vary. Therefore, should the definitions of cumulative (dis)advantage also consider the probability of experiencing the (dis)advantage?

Our definition of unconditional cumulative (dis)advantage, thus, 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 have higher educational attainment, thus the question is, weighting for that higher probability of additional advantage (high education), do the already privileged (Whites) gain more from high education. Under this unconditional 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.

Insight number two and the key feature of the unconditional 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.

The concepts conditional and unconditional cumulative (dis)advantage are complementary, and the concordance between the two definitions is weak. For example, we may observe cumulative disadvantage based on the conditional measure, but we observe neither cumulative disadvantage nor cumulative advantage on the unconditional measure. All other concordance and discordance combinations are also possible. 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 the conditional measure, some invariance exists across measurement scales: cumulative disadvantage on the absolute scale always implies the same cumulative disadvantage on the relative scale; and cumulative advantage on the relative scale always implies the same 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 unconditional measure we argue that the preferred scale is the absolute scale. The relative scale would require comparing probability-weighted ratios, which do not have an easy interpretation.

*2.2.3 Formal Notation for Cumulative (Dis)advantage*

[Table 1]

Here we formalize mathematically conditional and unconditional cumulative (dis)advantage. Table 1 describes the setting, as described above. The two-dimensional crosstabulations are (i) the levels of the outcome and (ii) 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. A−B and C−D are the difference in the outcome between low- and high-educated for Blacks and Whites, respectively. We call these, loss from lower education. The gain from high education is B−A for Blacks and D−C for Whites.

2.2.3.1 Conditional Definition

Conditional Cumulative Disadvantage (CCD) is a relationship between the two risk factors such that the disadvantaged lose more from having an additional disadvantage compared to the advantaged. In Table 1, column “Loss” shows the loss from lower education for Blacks, $A-B$, and for Whites, $C-D$. These are negative numbers. CCD is defined as $(A-B)<(C-D)$, the loss in magnitude in an absolute sense is larger for Blacks, compared to Whites. 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.

Conditional Cumulative Advantage (CCA) is a relationship between the two risk factors such that the advantaged gain more from having an additional advantage compared to the disadvantaged. In Table 1, column “Gain” shows the gain from higher education for Whites, $D-C$, and for Blacks, $B-A$. Under CCA, $(D-C)>(B-A)$, that is the gain in the outcome is larger for Whites than Blacks. The relation also implies that the racial penalty associated with being Black is larger among the high educated compared to the low educated.

CCD means no CCA; CCA means no CCD. Because CCD is defined by $(A-B)<(C-D)$ and CCA is defined by $(D-C)>(B-A)$[2], this mathematically implies they are mutually exclusive.[3]

Conditional definition and measurement scales: An alternative to the absolute scale is the relative scale under which CCD is defined as $A/B<C/D$ (“*Blacks lose proportionately more life expectancy than Whites from having a low education*”). Analogously, CCA on a relative scale is defined as $D/C>B/A$. As with the absolute scale, under the relative scale the data supports either CCD ($A/B<C/D$), or CCA ($D/C>B/A$), but not both.

Measurement scale matters. A finding of CCD on a relative scale does not imply a finding of CCD on an absolute scale. The two cases where consistency holds are as follows: first, when the data supports CCD on the absolute scale, it will also support CCD on the relative scale; and second, if the data supports CCA on the relative scale, it will also support CCA on the absolute scale.

We prove the first consistency directly and the other by contradiction. CCD on the absolute scale means that A−B<C−D. We argue that this implies A/B<C/D (relative scale definition):

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

We use the two equivalence relations

$$\mathrm{A}-\mathrm{B} \;<\; \mathrm{C}-\mathrm{D} \Leftrightarrow \mathrm{B}-\mathrm{A}>\mathrm{D}-\mathrm{C}$$
$$\frac{\mathrm{A}}{\mathrm{B}}<\frac{\mathrm{C}}{\mathrm{D}} \Leftrightarrow \frac{B}{A}>\frac{D}{C}$$

to rewrite the implication to be proven as

$$\mathrm{B}-\mathrm{A}>\mathrm{D}-\mathrm{C} \;\Rightarrow\; \frac{B}{A}>\frac{D}{C} \tag{2}$$

The proof is then simply

$$\frac{B}{A}=\frac{A+(B-A)}{A}>\frac{A+(D-C)}{A}=1+\frac{D-C}{A}>1+\frac{D-C}{C}=\frac{C+D-C}{C}=\frac{D}{C} \tag{3}$$

where step 3 follows from CCD on the absolute scale. In step 4, one of the underlying assumptions for positive outcome measures, $A<C$, was used (see Table 1).

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

#### 2.2.3.2 Unconditional Definition

Unconditional Cumulative Disadvantage (UCD) combines the likelihood and magnitude of disadvantage for expected loss. The expected loss (L) for Blacks (b) is $Lb=a/(b+a)*(A-B)$; that is, the probability of having low education times the loss from low education.[4] For Whites (w) this is $Lw=c/(c+d)*(C-D)$. UCD is defined as $Lb<Lw$, that is those already disadvantaged – Blacks – have a larger expected loss than Whites.

Unconditional Cumulative Advantage (UCA) combines the likelihood and magnitude of advantage for expected gain. The expected gain (G) for Whites is $Gw=d/(d+c)*(D-C)$ and for Blacks $Gb=b/(b+a)*(B-A)$. UCA is defined as $Gw>Gb$, that is those already privileged – Whites – have a higher expected gain from high education than Blacks.

The data can support both UCD and UCA, neither of them, or only one: In contrast to the conditional definition, in which support for one (CCD or CCA) is evidence against the other, in the unconditional case, we cannot infer anything about UCD/UCA, even if we know that one form of UCD or UCA exists. Appendix A illustrates this with examples.

Unconditional and conditional definitions do not map onto each other: The integration of probabilities in the unconditional definition means that there is no straightforward mapping between the conditional and unconditional definition. This is best illustrated by examples in which there is CCA on both absolute and relative scales, but UCD on the absolute scale (Appendix A).

*2.2.4 Temporal Accumulation*

The conditional and unconditional definitions have different implications on whether the process of accumulation is considered to be temporal or not and provide complementary perspectives to (dis)advantage. Using cumulative disadvantage as the example, consider first the unconditional definition that asks: given one disadvantage, what is the likelihood of attaining 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 unconditional definition therefore corresponds to the temporal formulation of the cumulative (dis)advantage concept, much as Merton's original conception (1968, 1988).

The conditional 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 conditional 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. CCA/CCD, thus, is more aligned with the "Blau-Duncan," status-resource interaction approach (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 conditional cumulative (dis)advantage. The direction of the regression interaction – either magnifying or attenuating the disadvantage of the already disadvantaged – reveals whether the data support conditional cumulative disadvantage or advantage. The "additive versus multiplicative" concept can further be extended to the unconditional 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 conditional definition of 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, 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 cognitive impairment, as Alzheimer's disease – one of the primary pathologies that causes cognitive impairment – is the one of the top and fastest-growing causes of death in many high-income countries.

## 2.3 Cognitive impairment through the lenses of intersectionality and cumulative (dis)advantage

An estimated 6.2 million Americans over age 65 have Alzheimer's disease (AD)—the incurable disease that is the most common cause of dementia and the sixth leading cause of death in the U.S. (Rajan et al. 2021). In 2021, health care, long-term care, and hospice (but not unpaid caregiving) for elders over age 65 with dementia was estimated to cost $355 billion (Alzheimer's Association 2021). Dementia is so costly because it often requires extensive care, often for years of declining functional abilities (Hurd, Martorell, and Langa 2015). These personal, social, and economic costs are not distributed evenly across the population. The burden of dementia is born disproportionately by women, Blacks, Latinx, and the lower-educated (Mayeda et al. 2016; Zhang, Hayward, and Yu 2016). Grounded in theories of intersectionality and cumulative (dis)advantage, we assume these one-dimensional risk factors have meaningful interactions. 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 cognitive impairment—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).

The social risk factors that appear most highly correlated with later-life cognitive function are race/ethnicity, childhood adversity, and educational attainment (Leggett et al. 2017; Mayeda et al. 2016; Zhang et al. 2016). Lifetime risk of cognitive impairment, mean age at first impairment, and years spent cognitively impaired are all strongly patterned by race/ethnicity (Hale, Schneider, Mehta, et al. 2020). Inequities in educational and occupational attainment only explain part of the racial/ethnic differences in cognitive health. Indeed, Black and Latinx Americans have higher risk of cognitive impairment, even net of educational level and other measured life course factors, such as early-life socioeconomic status (SES), later-life wealth, health behaviors (smoking, drinking, exercise), and chronic morbidities (Hale 2017; Zhang et al. 2016). The unexplained portion may be due to measurement issues, e.g., quality of education is inconsistent across racial/ethnic groups (Glymour and Manly 2008) and difficulties in adjusting for wealth inequities through standard survey measures (Conley 1999). Blacks and Latinx may also experience higher allostatic load, related to race-related stressors like racial discrimination (Das 2013; Geronimus et al. 2010; Williams and Mohammed 2013).

There is a large body of literature showing the association between early life and later-life health, disability, and mortality (e.g., Friedman et al. 2015; Lorenti et al. 2020; Montez and Hayward 2014). This applies also for cognitive impairment: early life experiences and conditions predict later-life cognitive function, either directly or indirectly (Hale 2017; Turrell et al. 2002; Zeki Al-Hazzouri et al. 2011). Similarly, education matters. Higher education is associated with lower risk, delayed onset, and decreased share of life expectancy spent cognitively impaired (Crimmins et al. 2018; Hale, Schneider, Mehta, et al. 2020; Reuser, Willekens, and Bonneux 2011). Part of the mechanism is likely related to having a larger reserve capacity that is both structural and functional (Jones et al. 2011; Valenzuela and Sachdev 2006). In other words, even if higher educated individuals develop underlying pathology that would be detectable in a brain scan or autopsy, they may not pass a clinical threshold of cognitive decline until an older age or, perhaps, not prior to death from another cause. Protective effects of higher education may also include opportunities for cognitively-stimulating environments across the life course, which are also insulative against cognitive decline (Reed et al. 2011).

Although there are gender disparities in cognitive impairment, with women having higher lifetime risk and more years cognitively impaired, they have an older mean age at onset (Hale, Schneider, Mehta, et al. 2020), which highlights that a portion of the disparity is related to women's longer life expectancy. Women in birth cohorts who have reached peak at-risk ages for cognitive impairment also have different risk profiles to men in terms of lower educational and occupational attainment, and they are more likely widowed (all higher risk), yet they have more extensive, supportive social networks (lower risk) (Fratiglioni et al. 2000; Schafer and Vargas 2016).

Much of the literature tests the individual relationships between cognitive impairment and each (or a couple) of these social factors. However, less is known about how these risk factors intersect or accumulate to produce disparities, despite research showing the importance of these interactive effects on other health outcomes (Brown 2018; Mehta and Preston 2016). There is some evidence for conditional cumulative disadvantage (CCD) with regard to cognitive function. Reuser and colleagues (2011) state that the cognitive penalty of being lower educated is larger for Blacks than Whites—CCD. Barnes and colleagues (2011) also find CCD: lower-educated Blacks pay a higher penalty for their lower education, but they highlight the implied reverse: Blacks with higher education benefit (in terms of lower risk of cognitive impairment in later life) more from their years of education than their White counterparts. Hale (2017) finds evidence for CCD for Latinx and Blacks.

In research on other health outcomes, such as low birth weight, infant mortality, and mortality due to certain cancers, Black Americans and Mexican Americans do not gain as much protection from higher SES as White Americans (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—CCA in our terms. Again, this is the antithesis of CCD, as it mathematically requires that Blacks/Latinx do not lose more from lower education.

Our analyses build on existing research and extend knowledge on cognitive impairment in several important ways. To understand how risk factors intersect to produce inequities in the burden of cognitive impairment, it is important to understand the dynamics of cognitive impairment. We estimate three innovative and complementary metrics that together provide a comprehensive picture of cognitive disparities at the intersections of four axes of inequality: race/ethnicity, nativity for Latinx, gender, and education. We use the frame of intersectionality and predictions derived from cumulative (dis)advantage to evaluate these interactions. Using incidence-based Markov multistate methods, we estimate for Americans aged 50 or older: (i) the lifetime risk of cognitive impairment, (ii) at what age, on average, individuals first become impaired, and (iii) cognitive health expectancies. We analyze both severe and mild cognitive impairment (MCI). Finally, we believe we are the first to go into depth regarding several complexities of understanding cumulative (dis)advantage: (i) differentiating CA/CD, (ii) defining conditional versus unconditional CA/CD, and (iii) including analyses of both absolute and relative measures.

## 3 Data and Methods

Using the Health and Retirement Study (HRS) data and multistate life table methods, Hale et al. (2020) documented an uneven burden of cognitive impairment across gender, race/ethnicity, and educational attainment, by analyzing the dimensions independently of each other. We extend the scope of that analysis and formally examine cumulative (dis)advantage along multiple dimensions. In many other respects, data, variable definitions, and analytical methods are in close analogy to the descriptions made in that reference paper. Here we provide a summary of the information given there as well as additional detail where the current analysis demands it.

### 3.1 Data

We use the HRS, a nationally representative longitudinal survey of U.S. residents aged 50 and older 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 measures on demographics, family, health, and wealth is collected. We use RAND Version 2018-V1 of the HRS, which covers the years up to 2018 for all variables except for cognition, for which the data end in 2016. We additionally use data on the Langa-Weir Classification of Cognitive Function, version 3.0, for the 2018 cognitive function data (Langa et al. 2022). All cognition data contain imputations for missing values of cognitive function scores (Fisher et al. 2017).

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 age 50. We analyze transitions, thus we only include subjects for whom there are at least two cognitive scores or a cognitive score followed by death. We exclude observations with missingness on gender, race/ethnicity, or education (0.6%). The resulting sample size is 32,870 individuals with more than 200,000 person-waves.

### 3.2 Variable definitions

The dependent variable, cognitive status, determines the state-space of the multistate model of the analysis. It consists of three transient cognitive states -- no cognitive impairment (NCI), cognitively impaired but not dementia (CIND), and dementia -- and one absorbing state (death;

recorded as reported by the HRS). Cognitive classification is based on selected components of the HRS's modified Telephone Interview for Cognitive Status (TICS) with a total range of 0 to 27 points. The components are immediate and delayed recall (0-10 points each), serial-7s (0-5 points), and backward counting from 20 (0-2 points); lower scores are indicative of lower cognitive function. The ranges of total scores that map into cognitive states are: 12-27 (NCI), 7-11 (CIND), and 0-6 (dementia). The corresponding score thresholds are well-established in the literature since they have been validated against the clinical assessment from the Aging, Demographics, and Memory Study (ADAMS) (Crimmins et al. 2011). To mitigate selection into self-interview by cognitive status we retain proxy interviews in our analyses (Langa et al. 2017). Components of the proxy measure are the proxy's assessment of the respondent's memory (0-4 points), the respondent's limitations regarding instrumental activities of daily living (0-5 points), and the respondent's cognitive ability to complete the HRS interview (0-2 points). We again use established and ADAMS-validated cut-points for classification (scores: NCI 0-2, CIND 3-5, dementia 6-11; higher scores are indicative of more severe impairment).

The set of independent variables consists of gender, reported as binary (woman/man) by the HRS, race/ethnicity, educational attainment, exact age at interview, the number of previous test occasions, and childhood adversities. We combine self-reported information on race/ethnicity into Non-Hispanic White, African American/Black Hispanic (following Chinn and Hummer 2016; Elo, Mehta, and Huang 2008), Non-Black Hispanic, and "Other", 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. 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+). We control for the number of cognition tests in order to control for practice effects, a form of panel conditioning (Hale, Schneider, Gampe, et al. 2020), using a categorical control variable with categories: first, second, third through sixth, and seven or more tests (Goldberg et al. 2015). We reserve a separate level of the control variable for proxy responses. The variable is lagged by one wave to assign values to the variable when the respondent died, which otherwise would be missing.

### 3.3 Analytic strategy

We use predicted probabilities from multinomial logistic regression models in conjunction with discrete-time Markovian multistate life table techniques (Millimet et al. 2003; Schneider 2021)[6] in order to calculate lifetime risk of impairment, mean age at first impairment, and state-specific durations (cognitive health expectancies).

The analytic chain consists of four steps. First, we estimate multinomial logistic regression models, using separate samples for each of the three non-absorbing initial states (NCI, CIND, dementia) and for each gender. The model is

$$(1) \qquad \log\left(\frac{p_{ij}}{p_{iN}}\right) = a_{ij} + b_{1,ij}\, Age + \; b_{2,ij}\, Age^2 + b_{3,ij} PE + \boldsymbol{\gamma_{ij}} \cdot DEMOGR\_IACT,$$

where $p_{ij}$ is the probability of transitioning from state $i$ to state $j$ (including death); $j=N$ indicates the reference target state (NCI); and the right-hand side includes the intercept, a linear and quadratic term for age, the number of prior tests taken (practice effect PE), and a full set of interactions of race/ethnicity (including nativity for Latinx) with education (DEMOGR_IACT). In Section 4.2 of the empirical analysis, the regressor term of main interest, DEMOGR_IACT, is a full two-way interaction. In Section 4.3, we extend DEMOGR_IACT to include a three-way interaction between race/ethnicity, education, and childhood adversities.

Second, we use the estimated multinomial regression models to generate transition probabilities for the age range 50-110 for each of the twelve combinations of states of origin (NCI, CIND, dementia) and destination states (additionally, death). This is done separately for the subpopulations implied by the combinations of gender, race/ethnicity, and education, and 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”). In some cases, averages are calculated across one or more dimensions (e.g., “All men”). Here, predictions are performed at sample averages. Practice effect is set to the second interview.

Third, we address measurement error in cognitive impairment that may influence in particular our analysis of lifetime risk and mean age at first incidence. Random measurement error has little impact on years lived in various states because positive and negative errors cancel out. Random measurement error however may result in “onset” being estimated to occur too young and “lifetime risk” too high because one single measurement with a low score would result in an individual being classified as cognitively impaired. We follow the strategy of Hale et al. (2020) to address misclassification of states by modifying life histories simulated from the estimated transition probabilities. The modifications are based on definitions of CIND and dementia onset, both of which we require to have two contiguous observations in the respective state. We allow for recovery from CIND, but not from dementia. Modifications cannot be applied to the dependent variable directly since complete life histories are necessary for the consistent application of the above impairment onset definitions. Detailed discussion on the simulation procedure is given in Appendix E.

Finally, in the fourth analytical step we use multistate Markov chain modeling techniques to calculate the three metrics of (i) the lifetime risk of any impairment or dementia, (ii) the mean age at first incidence of any impairment or of dementia, and (iii) expected length of stay in the states NCI, CIND, dementia, and total. The baseline age for all measures (i)-(iii) is 50. Descriptions of how to calculate metrics (i) and (ii) can be found in Dudel (2018) and Roth and Caswell (2018). Both measures are conditional on not being impaired at age 50. For metric (iii) we use the standard approach for estimating expectancies by first calculating expectancies conditional on a starting state at age 50 and then forming a weighted average across the conditional expectancies. The weights correspond to the empirical state distribution at age 50; however, to reduce small sample noise, we take the average over the age interval 50-59. For each race/ethnicity, gender, and education group, we use its own state distribution at age 50. Note that differences in cognitive expectancies reflect both differences in transition probabilities across the states, as well as initial differences in the state distribution at age 50.

We obtain 95% confidence intervals by bootstrapping (500 replications). Each bootstrap replication contains the entire analytic chain of regression estimation, probabilities prediction, simulation and modification of life histories, and the calculations of the outcomes based on the simulated data.

*3.3.1 Analyses including childhood adversities*

Our first analysis excludes childhood adversities. In Section 4.3, we add this dimension. 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 components 2-7, as defined above (but excluding blue-collar father, which characterizes more than three-quarters of the sample) divided into categories 0-1/2+; a cumulative count of components 1-7 divided into categories 0/1-4/5+; the count of 1-7 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 empty cells in the interacted variables by having a sufficient number of observations in the lowest (36%) and highest categories (21%). Here, low hardship 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 hardship category is defined by poor childhood health or by the respondent's father having a blue-collar job plus three other hardships. 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. Only 60 additional transitions are lost due to missingness compared with the sample of Section 4.2.

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 32,000 individuals. If we somewhat optimistically 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 32,000/(4^4)=125 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 30.[8]

The first consequence of the diminishing effective sample size is that including childhood adversity means that we must focus on the outcome that maximizes statistical power. That outcome is life expectancy. We calculate the outcome (total life expectancy) directly from the transition probabilities, omitting the simulation step. This permits the construction of confidence intervals via a novel analytical method developed by the authors [blinded], rendering the computationally expensive bootstrap obsolete.

The second consequence is that even with the outcome life expectancy, we must combine some of the dimensions to maintain statistical power. We simplify race/ethnicity by dropping "Other" and by combining US-born and foreign-born Latinx, despite being aware they have different cognitive health profiles (Garcia et al. 2017). We also had to 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.

The third consequence is that even after these power-preserving maneuvers, the data is 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 2 presents the composition of the sample (1998-2018), including the percentage of person-waves in non-impairment (75%), CIND (17%), and dementia (8%). The average age is 67 years. Women contribute 53% of the observations. Gender disparities in CIND (men slightly more) or dementia (women slightly more) are not large. However, there are substantial racial/ethnic, childhood adversity, and educational disparities in CIND and dementia prevalence. Blacks (26% CIND and 11% dementia), US-born Latinx (23% CIND and 9% dementia), and foreign-born Latinx (26% CIND and 9% dementia) have approximately double the prevalence of Whites (11% and 4%). The lowest educated compared with the highest educated have almost six and 10 more person-waves in CIND and dementia, respectively. The number of childhood adversities is higher in the CIND and dementia states (on average, 2.3 adversities) compared to the no-impairment state (1.7 adversities).

Table 2's lower panel presents the transitions among cognitive function states.[10] Most remain in the source state (NCI-NCI 84%, CIND-CIND 40%, dementia-dementia 47%). There is, however, a relatively large fraction moving from CIND back to non-impairment (34%). Transitioning from the dementia state to death (31%) is eight times (4%) and three times (11%) more likely than from NCI and CIND, respectively.

[Table 2]

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

### *4.2.1 Conditional Cumulative (Dis)advantage*

Prior research shows that gender, racial/ethnic, and educational disparities in cognitive impairment are large (Hale, Schneider, Mehta, et al. 2020). Therefore, instead of focusing on the main effects, we will focus on the questions of intersectionality and cumulative (dis)advantage. 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? We do not yet factor in the *likelihood* of experiencing an additional (dis)advantage.

For each of the three metrics, we present a figure showing the outcome for both any impairment and dementia. Table 3 summarizes the results in terms of cumulative (dis)advantage for all three metrics using "any impairment," which is a combination of CIND and dementia, as the outcome (results for dementia only are shown in Appendix C). The table shows first the educational differences in any cognitive impairment for each of the subpopulations, and then indicates when the difference points towards conditional cumulative advantage, when towards conditional cumulative disadvantage. Table 3 also complements each figure by showing educational differences on the absolute scale (left-hand columns) and the relative scale (right-hand columns).[11]

Due to the large number of factors involved,[12] our text focuses only on key contrasts. Likewise, to aid in succinct interpretation, if the empirical results consistently indicate advantage (or disadvantage) regardless of using the absolute or the relative scale, we will focus on the absolute scale for simplicity.

4.2.1.1 Lifetime risk of cognitive impairment

Figure 1 shows the lifetime risk of any cognitive impairment (Panel A) or dementia (Panel B) at age 50 among those who are non-impaired at age 50 (Appendix D for confidence intervals). Table 3 presents the associated benefit[13] in reduced lifetime risk of having at least an Associate degree compared with less than a high school diploma for the different subgroups (Panel A), as well as whether that evidence implies conditional cumulative advantage or disadvantage (Panel B).

**Any impairment.** Panel A of Figure 1 underscores that while educational attainment is strongly associated with lifetime risk, with a clear educational gradient within all groups, we also observe that within each educational attainment level, Blacks and Latinx have a higher risk compared with Whites. This pattern underscores that educational attainment does not fully explain differences between Whites, Blacks, and Latinx. The lowest educated Black women and Latinas, regardless of birth origin (henceforth “all Latinas”), have 16 to 19 percentage points (pp) higher risk of any impairment compared to their White counterparts. For example, low-educated Black women have 90% lifetime risk of cognitive impairment, while Whites have 73% risk. The racial/ethnic disparity for lower-educated men is not quite as dramatic, but still 9pp (Whites, 72% vs. Blacks, 81%) to 16pp (Whites, 72% vs. foreign-born Latinos, 88%). At the highest education levels, the racial/ethnic disparity is 5pp (White vs. Black women) to 28pp (White vs. foreign-born Latinos). It is clear even from these simple calculations that educational attainment operates differently dependent on race/ethnicity, nativity, and gender.

Table 3 demonstrates this educational gain (loss) for each subgroup, as well as its conceptual implications in terms of cumulative (dis)advantage. For example, the educational loss is larger for Black women (24pp) and Latinas (US-born 27pp, foreign-born 21pp) than for White women

(16pp), which supports conditional cumulative disadvantage (CCD) and therefore is evidence against CCA. In contrast and from a CCA perspective, for men higher education is associated with a larger reduction in lifetime risk of cognitive impairment among Whites (28pp) than Blacks (25pp), US-born Latinos (23pp), and foreign-born Latinos (16pp). These disparities are evidence for cumulative advantage among White men.

This advantage for White men is highlighted further when examining the intersection of gender and education by race/ethnicity/nativity. The gender disparity in educational gain for Whites is 12pp to White men's advantage (28pp – 16pp=12pp), whereas it provides only about 3pp and 5pp gain to US-born and foreign-born Latinx (with the greater gain to women) and no discernable gender difference in gain for Black men versus women.  In other words, education differentiates men and women more when they are White.

In sum, Table 3 Panel 2 shows that for lifetime risk Black women and all Latinas gain more from higher education than White women (16pp), but less than White men (28pp). As we know from Table 1, this also implies they lose more from lower education, which is consistent with CCD. This holds for both the absolute measurement (lefthand columns) and for proportional measurement (righthand columns).[14] Among men, however, the pattern is the opposite, and for each contrast and for both the absolute and relative scales, the data supports CCA: White men gain more from high education than other groups.

**Dementia.** Panel B of Figure 1 demonstrates some notable exceptions to the above pattern when dementia is the outcome. White women, Black women and men, and non-US-born Latinas all show the expected racial/ethnic and educational gradients in lifetime dementia risk such that lower education and racial/ethnic disadvantage is associated with higher risk. However, unexpectedly, highly educated Black men and US-born Latinos show similar or lower risk of dementia (14%, 19%, respectively) compared with their White counterparts (19%). Similarly, highly educated Black women and foreign-born Latinas have only slightly higher risk compared with White women. Part of this may be explained by the fact that high-educated and Whites have higher life expectancy than Blacks and US-born Latinx, which, all else equal, will increase lifetime risk.

Both White women and men gain less from higher education in terms of dementia risk reduction than Blacks and Latinx. Black men, US-born Latinos, and foreign-born Latinas with the highest education have less than half the risk compared with their lower-educated counterparts. In other words, in terms of dementia risk reduction, Black men and women, foreign-born Latinas, and US-born Latinos appear to gain more from their higher education than their White counterparts. This is evidence CCD because gaining more from education implies losing more from lower education.

[Figure 1]

[Table 3]

4.2.1.2 Mean age at first impairment

**Any impairment.** Figure 2 shows the gender, racial/ethnic, nativity, and educational disparities in mean age at any impairment and dementia (Appendix D for confidence intervals). The overall gender differences in mean age at first impairment appear small. Within educational categories, Whites experience an older age at onset than Blacks and all Latinx. Indeed, middle-educated White women have the same or later age at onset as the *highest* educated Blacks and Latinas. Men show a similar pattern with the exception of the highest educated foreign-born Latinos.

Table 3 Panel A shows that within racial/ethnic groups, attaining higher education is associated with 13-16 years postponed onset for all women subgroups. Among men, the gain is lower, ranging from 10 (foreign-born Latinos) to 13 years (White men). Panel B summarizes the results in terms of cumulative (dis)advantage. Among women, the results predominantly point towards CCD. US-born Latinas are the exception: high education is associated with a longer postponement of age at first impairment among Whites than among US-born Latinas, thus the data is consistent with CCA on the absolute scale. The differences in years postponed are, however, minor, 13.6 years among White women, 13.4 years among US-born Latinas. For men the pattern is the same as for lifetime risk of impairment: for each subpopulation and for both measurement scales, the data indicate White men experience CCA.

Comparing women vs. men subgroups (i.e., not explicitly shown in the table), higher education delays impairment about four to five years longer for foreign-born Latina (14 years) and Black women (16 years) compared with men (Latinos 10 years, Black men 11 years), indicating a gender disadvantage to lower education for Black and Latina women. Thus, for mean age at first impairment, we can see that women gain more from higher education than men, meaning they also lose more from lower education. This implies CCD for women (though for White women, it is negligible).

[Figure 2]

**Dementia.** For dementia, the story is a bit more complicated (Figure 2 Panel B). All women continue to have an older age at first impairment than men, the educational gradient remains, and Whites have later onset than Blacks and US-born Latinx. Lower-educated Black women (73 years) and US-born Latinas (75 years) experience dementia onset 6 and 4 years younger than their White counterparts (79 years). Among men, the differences are 5 and 3 years. However, foreign-born Latinx have similar or older onset compared to their White, same-education counterparts. Higher education for women is associated with a dementia delay of 8 (White) to 11 years (foreign-born Latinas), whereas for men the range is 4 (foreign-born Latino) to 12 years (Black). The gender disparities in the penalty for lower education are only substantial for foreign-born Latinx (Latinas 89-78=11 and Latinos 82-78=4). That foreign-born Latinas and Black men and women gain more from their higher education than Whites, again, implies that they lose more from lower education (CCD).

#### 4.2.1.3 Total life expectancy and cognitive health expectancies

Figures 3 and 4 highlight the substantively and statistically (Appendix D) important gender, racial/ethnic, nativity, and educational disparities in cognitive health expectancies. The educational differences are large within each subgroup: all subgroups with an Associate degree or higher have approximately 1.5 to more than two times the cognitively healthy years of those with less than high school, and less than half the years of cognitive impairment despite their longer total life expectancies.

It is also important to consider *share* of total life expectancy spent in states of poor health (Figure 4). Measuring disparities in health expectancies in this way provides a slightly different perspective on the burden of disease, e.g., what is the burden of spending 10 years longer in a state of impairment for those who have a total life expectancy at age 50 of 23 years (Black, low-educated men) compared with 36 years (White, high-educated women)? The former spend more than half of their remaining life expectancy in a state of impairment compared with less than 12% for the latter.

Table 3 shows that among women, Latinas and Blacks lose more from lower education (or gain more from high education) than Whites both in terms of absolute years spent unimpaired and share of unimpaired life expectancy. For example, the educational penalty in years (share reduction) of life expectancy cognitively impaired is 15 years (38pp) among foreign-born Latinas, 15 years (42pp) among Black women, and 13 years (20pp) among White women. That lower education penalizes Black and Latina women more than White women indicates CCD. Among men, the pattern of CCD across racial/ethnic groups holds only partially. Whites gain more unimpaired years from high education than Latinos, indicating CCA. However, in terms of share of unimpaired life from total life expectancy, White men lose the least from low education, indicating CCD for Blacks and Latinos.

[Figure 3 and 4]

In sum, we find that, compared with White women, Black women and all Latinas are penalized more from having low education in terms of their lifetime risk, mean age at first incidence, and cognitive health expectancies; this is true whether measuring on the absolute or the relative scale (Table 3). This is overwhelming evidence for Black women and Latinas experiencing <u>conditional cumulative disadvantage</u>.

We find that White men generally gain more from high education than their Black and Latino counterparts. The exception is share of unimpaired life years gained from high education. For this outcome, the data is consistent with CCD. This can be understood best through example. Even if Latinos gain fewer years from high education than White men (in years: foreign-born 12.1, US-born 9.5, White 12.5), this smaller gain in number of years is a larger gain in proportion of life expectancy (in pp: foreign-born 33, US-born 29, White 26), as the overall life expectancy among

Latinos is lower than among White men. For the most part, though, the evidence predominantly points to White men experiencing conditional cumulative advantage.

### *4.2.2 Unconditional Cumulative (Dis)advantage*

Unconditional cumulative (dis)advantage introduces into its assessment 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 4 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 reduction in lifetime risk, postponement of age at first impairment, increase in unimpaired years, and increase in proportion of remaining life unimpaired.

The lefthand side results (low-educated weights) show that if one combines both the likelihood of attaining lower education and the increased health risk associated with low education, Blacks and both Latinx groups are expected to lose more from low education than Whites. This holds for women and men and for all metrics of cognitive impairment that we estimate. Thus, taking into consideration the high probability of a Black or Latinx person attaining low education yields a consistent story of cumulative disadvantage.

This finding should be interpreted in conjunction with the results of Table 3 that showed the *conditional* cumulative (dis)advantage patterns. While the conditional measure also suggested disadvantage for women in almost all cases (23/24) and for men in some cases (9/24), for some outcomes the data implied only cumulative advantage. For example, lifetime risk of any cognitive impairment is patterned such that White men gain more than Blacks and all Latinos from higher education (CCA); or conversely, Blacks and Latinos lose less from low education than White men. However, the unconditional definition acknowledges that Blacks are more likely to have low education; hence, when based on the unconditional definition, evidence points to cumulative disadvantage.

The unconditional definition also suggests that for most comparisons the data is consistent not only with cumulative disadvantage, but also with cumulative advantage. The righthand side of Table 4 shows that unconditional cumulative advantage holds for men in all comparisons and in most of the comparisons for women (10/12). The interpretation for the almost-omnipresent cumulative advantage pattern on the unconditional metric is that even if for some health outcomes Blacks or Latinx might gain more than Whites from higher education, their likelihood of attaining high education is so much lower that Whites still have cumulative advantage (Table 4).

In sum, if we account for the likelihood of acquiring the additional disadvantage for Blacks and Latinx, cumulative disadvantage always results, and if we account for the likelihood of gaining an additional advantage for Whites, cumulative advantage predominantly results.

[Table 4]

### 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 focused only on total life expectancy, and 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 eight specifications for estimating the four-dimensional interactions that include childhood adversities. Unless otherwise noted, all models use a measure that is based on a cumulative count of adverse childhood circumstances and a full four-way interaction of gender-education-race/ethnicity-childhood adversity, where the interaction by gender is implicit since samples are split by gender. The first four specifications (I)-(IV) sequentially pick one of the operationalizations of childhood adversity described in the methods section above. Model (I) uses the six-component count divided into two levels (0-1/2+). Model (II) uses the seven-component count (including the blue-collar indicator for father's occupation) categorized as 0, 1-4, and 5 or more. This measure is better suited for detecting effects that only materialize at the tails of the adversity distribution. Model (III) uses the same adversity count, but it enters the interactions linearly, allowing each cell to have its own intercept and slope. It therefore estimates the same number of parameters as model (I). Model (IV) uses the three-category hardship variable that features a higher percentage of observations in the lower and upper levels compared to that used in Model (II), and therefore is more likely to deliver reliable estimates of the interacted effects of childhood adversities.

Models (V)-(VII) further explore the categorization used in model (IV). Model (V) imposes custom constraints based on an examination of cells that still have low counts. All cells with five for fewer observations receive a restriction. This results in 14 custom constraints, which is still a small number, considering that many of the models estimate a total of 380 parameters. Model (VI) imposes stronger restrictions than these few custom constraints. It restricts the number of parameters by estimating only the three-way interactions gender-race/ethnicity-education and gender-race/ethnicity-adversity, leaving out gender-education-adversity, race/ethnicity-education-adversity, as well as the full four-way interaction. Model (VII) imposes less stringent restrictions. Based on a sample that is not split by gender, it contains all four possible three-way interactions, but not the deepest four-way interaction level. It thereby connects all four dimensions, yet does not rely on the most problematic four-way interaction cells.

Finally, the last model, model (VIII), makes use of an adversity measure that is solely based on a binary indicator for the level of parents' education (average education less than 10 years, or 10 years or more). The rationale behind this is parental education is predictive of the other hardships, and the cut at 10 years delivers an approximately equal split of the data, reducing statistical power concerns.

[Figure 5]

[Figure 6]

Figure 5 presents estimates of total life expectancy for only the lowest and highest childhood adversity categories for all of the 8 models, and Figure 6 plots 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 sub-populations. For example, among low-educated Latinas (top-right panel of Figure 5 and 6), Model II estimates that those without early life adversity have 6 years higher life expectancy. However, Model XIII for the same group estimates that no early life adversity is associated with 4 years lower life expectancy. For other specifications for this group, the estimates balance out, with three suggesting that more early life adversity predicts higher, and three predicting lower life expectancy. The pattern is equally mixed for both high- and low-educated Black women. Among high-educated White and Latina women, a pattern that suggests a protective effect associated with low early life adversity emerges. However, the magnitude of this association varies wildly across specifications: among White women from 0.5 years to 2.5 years and among Latinas from near zero to up to 5 years.

For men the patterns are equally inconclusive. For each of the sub-populations the results are mixed such that some models predict that low adversity is associated with high life expectancy and some models the opposite. For example, for low-educated White men, six out of eight model specifications predict that more early life adversity is associated with higher life expectancy, and two other models the opposite; however, for each of these contrasts, the statistical power is low. The sole exception is low-educated Black men among whom the models consistently predict that more early life adversity is associated with higher life expectancy. The magnitude of this association varies strongly from less than one year (Model VI) to almost 5 years (Model II), but all estimates are accompanied by large statistical uncertainty.

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 8 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 approach our research question of understanding the racial/ethnic, nativity, gender, and socioeconomic inequities in cognitive impairment amongst older people residing in the US through the lenses of intersectionality and cumulative (dis)advantage. 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 loosely in the literature.

In order to offer a clear foundation for our own analysis, we start by historicizing intersectionality and distinguishing between what we term “conditional” and “unconditional” cumulative (dis)advantage. By conditional, we mean the standard 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 conditions on individuals being positioned on two axes of (dis)advantage and focuses on outcomes. We work through a mathematical proof demonstrating that conditional cumulative advantage (CCA) and disadvantage (CCD) are mutually exclusive whether measured on an absolute or relative scale. Our proof demonstrates that Blacks either lose more from lower education (CCD) or Whites gain more from high education (CCA). They are mutually exclusive.

We next put forward a novel concept that we call "unconditional cumulative (dis)advantage" (UCD for disadvantage, or UCA for 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 lifetime risk of impairment, mean age at first impairment, and cognitive health expectancies. Our estimates take into consideration not just whether those with multiple disadvantages have worse cognitive outcomes than would be expected based on the intersection of their individual disadvantages (CCD/CCA; Table 3), but also the probability of acquiring additional (dis)advantages (UCD/UCA; Table 4).

In the second part of our analysis (Section 4.3), we include childhood adversities. Data constraints lead us to present, instead of our three planned metrics, a specification curve analysis of total life expectancy (TLE) using four different operationalizations of childhood adversity and eight model specifications. These analyses demonstrate the wild variability in TLE estimates even when substantially simplify models (Figures 5 and 6).

With three metrics for understanding cognitive health (lifetime risk, mean age at first impairment, cognitive health expectancies), two scales (absolute and relative), five sociodemographic risk factors (gender, race/ethnicity, nativity for Latinx, childhood adversity, and educational attainment), as well as a conditional and unconditional 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 or in appendices.

## 5.2 Interpretation

To summarize, all evidence points toward the importance of applying an intersectional lens in studying cognitive impairment in that the width, and sometimes even direction of, inequities depend on the intersections of these axes of privilege. Nevertheless, we find that Black and Latina women experience cumulative disadvantage across all metrics and regardless of measurement being on the absolute or relative scale (i.e., compared to Whites, lower education is worse for Blacks and Latinas and being Black or Latina is worse for the lower educated) (CCD and UCD). This holds except when we take into consideration White women’s higher probability of attaining higher education, in which case White women experience cumulative advantage—their higher education benefits them more (UCA).

In contrast, White men predominantly experience conditional cumulative advantage regardless of absolute or relative scale (with some exceptions); their education benefits them more than it does their Black and Latino counterparts. The converse is that those White men who do not manage to achieve higher education lose more than lower-educated Blacks and Latinos. That said, when using the unconditional definition, we find that factoring in the probability of those Black and Latino counterparts attaining lower education results in cumulative disadvantage, always (UCD). And, factoring in White men's higher probability of attaining higher education results in cumulative advantage, always (UCA).

### 5.3 Limitations

There are at least three 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 to 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, but is beyond the scope of the current paper.

Second, we assume that the outcome – cognitive impairment – is measured with similar accuracy across sub-populations. This assumption may not hold, as sensitivity and specificity of the test may be strongest among the largest sub-populations. The implications of this assumption may increase the uncertainty in our estimates beyond the statistical uncertainty that we report.

Third, our analysis of early life hardship 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 for cognitive impairment 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 conditional and unconditional 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 lifetime risk, age at first impairment, and (un)impaired expectancies. Third, we use incidence-based Markov chain multistate models to study the burden of cognitive impairment using three different metrics. This has significant advantages over prevalence-based methods, which are biased if incidence or mortality are changing as is the case for the period under investigation (1998-2018) (Barendregt, Bonneux, and Van der Maas 1994; Imai and Soneji 2007). Fourth, we incorporate a measure of childhood adversity and present a range of results related to 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 inequalities in cognitive impairment:

*Conditional Cumulative (Dis)Advantage* that reflects inequalities in outcomes, and *Unconditional Cumulative (Dis)Advantage* that additionally accounts for inequalities 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. Black women and Latinas experience *Conditional Cumulative Disadvantage*: they are penalized more from having lower education than Whites. White men, however, experience *Conditional Cumulative Advantage*: they benefit more from higher education than Blacks or Latinx. However, when accounting for inequalities in educational opportunities, results ubiquitously show *Unconditional Cumulative Disadvantage* for men and women. 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 inequities in cognitive impairment.

Notes

1. Extensions to more than two categories are possible. For the conditional approach, additional dimensions can be included as long as one conditions on these dimensions. For the unconditional approach, additional dimensions require taking the expectation over these additional dimensions.
2. Multiplying both sides of $A-B < C-D$ by $-1$ and rearranging, we get the condition "no conditional cumulative advantage", $A-B > C-D$. This shows that conditional cumulative disadvantage and conditional cumulative advantage are strictly opposing hypotheses.
3. We assume no strict equality, that is no $A-B = C-D$. If the outcome is categorical, strict equality may occur. Then the data supports neither of the definitions, not conditional 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. Those in the highest educational category have a loss of B-B=0. Therefore, the complete formula can be written as $Lb=[a/(b+a)]*(A-B)+[b/(b+a)]*0$, and analogously for Whites and gains. This (equivalent) formulation has two advantages: 1) It clarifies that the unconditional definition corresponds to the statistical concept of expected value; 2) It makes clear that the definition extends to more than two levels of a category. These additional levels can be treated by including them in the probability-weighted sum such that the loss (or gain) is evaluated over the whole distribution or by removing levels such that only two remain and scaling the probabilities for the remaining levels to sum to 1. In the empirical analysis where we have 3 levels of education, we adopt the latter strategy and focus on the high-low contrast in order to facilitate comparison to the conditional (dis)advantage measure.
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. (2021) 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 4,588 observations.

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/hd5gz/?view_only=165c6ff0cd6c4e7cb26595eb1376d453
10. Table 2 shows all transitions of the multinomial logit estimation sample, which differs from the transitions upon which the final results are based. This is because of the simulation step and the subsequent modification of simulated life histories according to our two-period impairment onset rules as laid out in “3 Data and Methods” and Appendix E. These modifications do not allow for recovery from dementia.
11. The numbers for the relative percentage change shown in the table are the ones relevant for the condition of CCA (or CCD) on the relative scale, minus one. The condition remains unchanged, of course. For CCA, 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 CCD.
12. With 24 intersections (4 race/ethnicity/nativity, 2 gender, 3 education levels) for each of the three metrics, disparities among those intersections, and measurement differences (e.g., years versus proportion), the number of potential comparisons is large. Readers who would like to focus on other intersectional disparities can use the figures and tables in the main text and appendices to glean further information.
13. It is important to note we are not making a causal argument; however, for simplicity, we use the expressions “educational gain” or “benefit” to mean that higher education is associated with a decrease in risk of cognitive impairment, an older age at first impairment, and/or more years in good cognitive health.
14. The proof that CCD on the absolute scale implies CCD on the relative scale assumes an outcome for which more is better. This is not true for lifetime risk. Therefore, the concordance shown in Table 3 is not guaranteed for this outcome, though empirically in our case it holds.

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# Appendix Tables and Figures

## A. Numerical Examples of Cumulative Advantage and Disadvantage

This section demonstrates the possibility of various co-occurrences of different types of cumulative advantage or disadvantage by means of numerical examples.

**Example 1:** Conditional cumulative advantage (CCA) on the absolute scale can coexist with conditional cumulative disadvantage (CCD) on the relative scale.

In the main text, we stated that CCD on the relative scale does not imply CCD on the absolute scale and that CCA on the absolute scale does not imply CCA on the relative scale. These two statements imply the possibility of the coexistence of CCA-absolute and CCD-relative.

The following data on age at first impairment are taken from Table 1 (any impairment) for US-born Latinas.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Latinx, US-born | 60.2 | 73.6 | 0.730 | 0.270 |
| White | 67.2 | 80.8 | 0.428 | 0.572 |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -13.4 | 13.4 | Disadvantage: | -13.4 < -13.6 | NO |
| White | -13.6 | 13.6 | Advantage: | 13.6 > 13.4 | **YES** |

**Relative Scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | 0.82 | 1.22 | Disadvantage: | 0.82 < 0.83 | **YES** |
| White | 0.83 | 1.20 | Advantage: | 1.20 > 1.22 | NO |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -9.8 | 3.6 | Disadvantage: | -9.8 < -5.8 | YES |
| White | -5.8 | 7.8 | Advantage: | 7.8 > 3.6 | YES |

**Example 2:** It is possible to have neither unconditional cumulative disadvantage nor unconditional cumulative advantage.

The following data on the unimpaired proportion of life are taken from Table A1 (dementia) and are for Black men. Cells marked with an asterisk have fictitious data so that the desired decisions are obtained.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Black | 73.2 | 95.5 | 0.225* | 0.775* |
| White | 87.9 | 96.6 | 0.620* | 0.380* |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | -22.3 | 22.3 | Disadvantage: | -22.3 < -8.7 | YES |
| White | -8.7 | 8.7 | Advantage: | 8.7 > 22.3 | NO |

**Relative Scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | 0.77 | 1.30 | Disadvantage: | 0.77 < 0.91 | YES |
| White | 0.91 | 1.10 | Advantage: | 1.10 > 1.30 | NO |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | -5.0 | 17.3 | Disadvantage: | -5.0 < -5.4 | **NO** |
| White | -5.4 | 3.3 | Advantage: | 3.3 > 17.3 | **NO** |

**Example 3:** Unconditional cumulative disadvantage can occur without unconditional cumulative advantage occurring.

Data are identical to the previous example, except that the two fictitious numbers have been replaced by the true ones.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Black | 73.2 | 95.5 | 0.660 | 0.340 |
| White | 87.9 | 96.6 | 0.349 | 0.651 |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | -22.3 | 22.3 | Disadvantage: | -22.3 < -8.7 | YES |
| White | -8.7 | 8.7 | Advantage: | 8.7 > 22.3 | NO |

**Relative Scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | 0.77 | 1.30 | Disadvantage: | 0.77 < 0.91 | YES |
| White | 0.91 | 1.10 | Advantage: | 1.10 > 1.30 | NO |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Black | -14.7 | 7.6 | Disadvantage: | -14.7 < -3.0 | **YES** |
| White | -3.0 | 5.7 | Advantage: | 5.7 > 7.6 | **NO** |

**Example 4:** Unconditional cumulative advantage can occur without unconditional cumulative disadvantage occurring.

Data are identical to the one from Example 1, except that the numbers marked by an asterisk below (all population fractions) are now fictitious numbers.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Latinx, US-born | 60.2 | 73.6 | 0.760* | 0.240* |
| White | 67.2 | 80.8 | 0.750* | 0.250* |

### Conditional cumulative advantage / disadvantage

#### Absolute scale

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -13.4 | 13.4 | Disadvantage: | -13.4 < -13.6 | NO |
| White | -13.6 | 13.6 | Advantage: | 13.6 > 13.4 | YES |

#### Relative Scale

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | 0.82 | 1.22 | Disadvantage: | 0.82 < 0.83 | YES |
| White | 0.83 | 1.20 | Advantage: | 1.20 > 1.22 | NO |

### Unconditional cumulative advantage / disadvantage

#### Absolute scale, probability weighted

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -10.18 | 3.2 | Disadvantage: | -10.18 < -10.2 | **NO** |
| White | -10.2 | 3.4 | Advantage: | 3.4 > 3.2 | **YES** |

**Example 5:** Unconditional cumulative advantage and unconditional cumulative disadvantage can both occur.

The following data on years unimpaired are taken from Table 1 (any impairment) and are for US-born Latinas.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Latinx, US-born | 13 | 25.7 | 0.597 | 0.403 |
| White | 19.2 | 31.8 | 0.428 | 0.572 |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -12.7 | 12.7 | Disadvantage: | -12.7 < -12.6 | YES |
| White | -12.6 | 12.6 | Advantage: | 12.6 > 12.7 | NO |

**Relative Scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | 0.51 | 1.98 | Disadvantage: | 0.51 < 0.60 | YES |
| White | 0.60 | 1.66 | Advantage: | 1.66 > 1.98 | NO |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -7.6 | 5.1 | Disadvantage: | -7.6 < -5.4 | **YES** |
| White | -5.4 | 7.2 | Advantage: | 7.2 > 5.1 | **YES** |

**Example 6:** Conditional cumulative advantage on both the absolute and relative scale are consistent with unconditional cumulative disadvantage.

The following data on age at first impairment are taken from Table 1 (any impairment) and are for US-born Latinos.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Latinx, US-born | 60.9 | 71.9 | 0.709 | 0.291 |
| White | 63.9 | 77.2 | 0.349 | 0.651 |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -11.0 | 11.0 | Disadvantage: | -11.0 < -13.3 | NO |
| White | -13.3 | 13.3 | Advantage: | 13.3 > 11.0 | **YES** |

Relative Scale

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | 0.85 | 1.18 | Disadvantage: | 0.85 < 0.83 | NO |
| White | 0.83 | 1.21 | Advantage: | 1.21 > 1.18 | **YES** |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-b. | -7.8 | 3.2 | Disadvantage: | -7.8 < -4.6 | **YES** |
| White | -4.6 | 8.7 | Advantage: | 8.7 > 3.2 | YES |

**Example 7:** Conditional cumulative advantage on the absolute scale and conditional cumulative disadvantage on the relative scale do not imply unconditional cumulative advantage or disadvantage.

Data are identical to the one from Example 1, except that the numbers marked by an asterisk below (all population fractions) are now fictitious numbers.

| | Outcome level | | Population fraction | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/ethnicity | Low | High | Low | High |
| Latinx, US-born | 60.2 | 73.6 | 0.400* | 0.600* |
| White | 67.2 | 80.8 | 0.750* | 0.250* |

**Conditional cumulative advantage / disadvantage**

**Absolute scale**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -13.4 | 13.4 | Disadvantage: | -13.4 < -13.6 | NO |
| White | -13.6 | 13.6 | Advantage: | 13.6 > 13.4 | **YES** |

Relative Scale

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | 0.82 | 1.22 | Disadvantage: | 0.82 < 0.83 | **YES** |
| White | 0.83 | 1.20 | Advantage: | 1.20 > 1.22 | NO |

**Unconditional cumulative advantage / disadvantage**

**Absolute scale, probability weighted**

| | Loss from low | Gain from high | Criterion | | Decision |
|---|---|---|---|---|---|
| Latinx, US-born | -5.4 | 8.0 | Disadvantage: | -5.4 < -10.2 | **NO** |
| White | -10.2 | 3.4 | Advantage: | 3.4 > 8.0 | **NO** |

# B. NEGATIVE OUTCOME MEASURES

The elaborations on cumulative (dis)advantage in the main text exclusively relate to positive outcome measures. This section extends results to negative outcome measures. Calculations, decision rules, and proofs mimic the ones from the main text, up to an occasional flip of sign or logic. Table A1 on the next page summarizes the results. The proof of the relationships stated at the bottom of the table is as follows:

a) Conditional cumulative advantage (CCA) on the absolute scale implies CCA on the relative scale, but not vice versa.

Under the assumptions of Table A1 about the relative levels of A, B, C, and D, one needs to prove

$$\mathrm{B} - \mathrm{A} > \mathrm{D} - \mathrm{C} \;\Rightarrow\; \frac{B}{A} > \frac{D}{C} \tag{A1}$$

Note that relation (A1) is identical to relation (2) of the proof for a positive outcome in the main text. What is different now are the assumptions about the relative levels of A, B, C, and D (compare Table 1 and Table A1). We take analogous steps to the proof for positive outcome measures and use the two equivalence relations

$$\mathrm{B} - \mathrm{A} > \mathrm{D} - \mathrm{C} \Leftrightarrow \mathrm{A} - \mathrm{B} \;<\; \mathrm{C} - \mathrm{D}$$

$$\frac{B}{A} > \frac{D}{C} \Leftrightarrow \frac{\mathrm{A}}{\mathrm{B}} < \frac{\mathrm{C}}{\mathrm{D}}$$

to rewrite the implication to be proven as

$$\mathrm{A} - \mathrm{B} \;<\; \mathrm{C} - \mathrm{D} \Rightarrow \frac{\mathrm{A}}{\mathrm{B}} < \frac{\mathrm{C}}{\mathrm{D}} \tag{A2}$$

Again, while relation (A2) is identical to relation (1) of the proof for a positive outcome, the difference lies in the assumptions about the relative levels of A, B, C, and D. The proof is:

$$\frac{A}{B} = \frac{B + (A - B)}{B} < \frac{B + (C - D)}{B} = 1 + \frac{C - D}{B} < 1 + \frac{D - C}{D} = \frac{D + C - D}{D} = \frac{C}{D}$$

where step 3 follows from CCA on the absolute scale. In step 4, one of the underlying assumptions for negative outcome measures, $B > D$, was used (see Table A1).

b) Conditional cumulative disadvantage (CCD) on the relative scale implies CCD on the absolute scale, but not vice versa.

We prove by contradiction: The statement that CCD is present on the relative scale and CCA on the absolute scale is in contradiction to the just proven implication. Since, under the given assumptions about the relative levels of A, B, C, and D (see Table A1), there must always be either CCD or CCA on the absolute scale, it follows that CCD on the relative scale implies CCD on the absolute scale.

Table A1 Definitions, calculations, and decision rules for cumulative (dis)advantage (negative outcome measures)*

| | **Levels of the outcome** | | **Population fractions** | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/Ethnicity | Low | High | Low | High |
| Black | A | B | a | b |
| White | C | D | c | d |

**Assumptions for a negative outcome** (e.g., lifetime risk; lower values are beneficial):
A>C, B>D : within education levels, Blacks have higher levels of the detrimental outcome
B<A, D<C : within race/ethnicity, higher education leads to lower levels of the detrimental outcome

| | **Educational differences** **Absolute scale** | | **Relative scale** | | **Probability weighted (abs. scale)** | |
|---|---|---|---|---|---|---|
| Race/Ethnicity | Loss from low educ. | Gain from high educ. | Loss from low educ. | Gain from high educ. | Loss from low educ. | Gain from high educ. |
| Black | A-B | B-A | A/B | B/A | a/(a+b) * (A-B) | b/(a+b) * (B-A) |
| White | C-D | D-C | C/D | D/C | c/(c+d) * (C-D) | d/(c+d) * (D-C) |
| Range of values | >0 | <0 | >1 | <1 | >0 | <0 |

**Decision rules, conditional definition, absolute scale:**
Cumulative disadvantage: A-B > C-D (Blacks fare worse (experience a greater increase in a detrimental outcome) from low education, conditional on education)
Cumulative advantage: B-A > D-C (Whites fare better (experience a larger decrease in a detrimental outcome) from high education, conditional on education)

**Decision rules, conditional definition, relative scale:**
Cumulative disadvantage: A/B > C/D (Blacks fare proportionally worse (experience a greater increase in a detrimental outcome) from low education, conditional on education)
Cumulative advantage: B/A > D/C (Whites fare proportionally better (experience a larger decrease in a detrimental outcome) from high education, conditional on education)

**Decision rules, unconditional definition, absolute scale:**
Unconditional cumulative disadvantage: a/(a+b)*(A-B) > c/(c+d)*(C-D) (Blacks fare worse from low education, but "in expectation")
Unconditional cumulative advantage: b/(a+b)*(B-A) > d/(c+d)*(D-C) (Whites fare better from high education, but "in expectation")

**Relationships among the different definitions:**
Conditional absolute advantage implies conditional relative advantage, but not vice versa.
Conditional relative disadvantage implies conditional absolute disadvantage, but not vice versa.
There is no relationship between conditional results and unconditional results.

*Complements Table 1 of the main text.

# C. Cumulative Advantage and Disadvantage for Dementia

The tables in this section provide information for dementia that is complementary to Table 3 and Table 4 of the main text, which show results for "any impairment" only.

Table A2 Conditional cumulative (dis)advantage: Panel A shows the benefit of higher education (Associates or higher vs. less than high school) in terms of either percentage point risk reduction (lifetime risk of dementia and proportion of life with dementia) or delay in years (age at dementia onset and years lived with dementia) on both absolute and relative (percent change) scales. Panel B shows whether evidence in Panel A implies conditional cumulative advantage (A) for Whites or cumulative disadvantage (D) for Blacks or Latinx, by nativity.

**Panel A**

| | Absolute (difference, pp*, or years) | | | | Relative (% change) | | | |
|---|---|---|---|---|---|---|---|---|
| | White | Black | Latinx, US-born | Latinx, non-US-born | White | Black | Latinx, US-born | Latinx, non-US-born |
| Women | | | | | | | | |
| Reduced lifetime risk, % | 4.7 | 23.1 | 8.0 | 35.3 | 13.6 | 41.0 | 13.4 | 51.8 |
| Postponed dementia onset, years | 8.4 | 10.6 | 8.6 | 11.3 | 10.7 | 14.5 | 11.4 | 14.6 |
| Additional dementia-free years | 9.4 | 9.8 | 7.1 | 9.6 | 38.0 | 49.2 | 31.0 | 37.8 |
| Increase in dem.-free % of life, pp. | 6.7 | 19.1 | 14.1 | 22.9 | 7.6 | 26.4 | 19.6 | 32.0 |
| Men | | | | | | | | |
| Reduced lifetime risk, % | 11.2 | 31.6 | 28.1 | 6.5 | 37.4 | 68.8 | 60.0 | 13.7 |
| Postponed dementia onset, years | 8.3 | 11.3 | 8.5 | 4.5 | 11.1 | 16.3 | 12.0 | 5.8 |
| Additional dementia-free years | 8.6 | 9.8 | 8.2 | 4.0 | 39.5 | 58.8 | 43.6 | 15.5 |
| Increase in dem.-free % of life, pp. | 8.8 | 22.3 | 14.7 | 11.8 | 10.0 | 30.4 | 18.6 | 14.3 |

*pp: Percentage Point

**Panel B**

| | Absolute | | | | Relative | | | |
|---|---|---|---|---|---|---|---|---|
| | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born |
| Women | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | D | . | D | A | D |
| Postponed dementia onset, years | . | D | D | D | . | D | D | D |
| Additional dementia-free years | . | D | A | D | . | D | A | A |
| Increase in dem.-free % of life | . | D | D | D | . | D | D | D |
| Men | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | A | . | D | D | A |
| Postponed dementia onset, years | . | D | D | A | . | D | D | A |
| Additional dementia-free years | . | D | A | A | . | D | D | A |
| Increase in dem.-free % of life | . | D | D | D | . | D | D | D |

Table A3 Unconditional cumulative (dis)advantage: Panel A shows the benefit of higher education (Associates or higher vs. less than high school) in terms of either percentage point risk reduction (lifetime risk of dementia and proportion of life with dementia) or delay in years (age at dementia onset and years lived with dementia) on both absolute and relative (percent change) scales. Panel B shows whether evidence in Panel A implies unconditional cumulative advantage (A) for Whites or cumulative disadvantage (D) for Blacks or Latinx, by nativity.

**Weighted (absolute) changes in outcomes**

| | Weights: Low Educated | | | | Weights: High Educated | | | |
|---|---|---|---|---|---|---|---|---|
| | White | Black | Latinx, US-born | Latinx, non-US-born | White | Black | Latinx, US-born | Latinx, non-US-born |
| Women | | | | | | | | |
| Weights: Associates+ (Adv.) or <HS (Disadv.), % | 42.7 | 59.7 | 72.9 | 85.7 | 57.3 | 40.3 | 27.1 | 14.3 |
| Reduced lifetime risk, % | 2.0 | 13.8 | 5.8 | 30.2 | 2.7 | 9.3 | 2.2 | 5.1 |
| Postponed dementia onset, years | 3.6 | 6.3 | 6.3 | 9.7 | 4.8 | 4.3 | 2.3 | 1.6 |
| Additional dementia-free years | 4.0 | 5.8 | 5.1 | 8.2 | 5.4 | 3.9 | 1.9 | 1.4 |
| Increase in dem.-free % of life, pp. | 2.9 | 11.4 | 10.3 | 19.6 | 3.8 | 7.7 | 3.8 | 3.3 |
| Men | | | | | | | | |
| Weights: Associates+ (Adv.) or <HS (Disadv.), % | 34.9 | 66.0 | 70.8 | 85.0 | 65.1 | 34.0 | 29.2 | 15.0 |
| Reduced lifetime risk, % | 3.9 | 20.9 | 19.9 | 5.6 | 7.3 | 10.7 | -8.2 | 1.0 |
| Postponed dementia onset, years | 2.9 | 7.5 | 6.0 | 3.8 | 5.4 | 3.8 | 2.5 | 0.7 |
| Additional dementia-free years | 3.0 | 6.4 | 5.8 | 3.4 | 5.6 | 3.3 | 2.4 | 0.6 |
| Increase in dem.-free % of life, pp. | 3.1 | 14.7 | 10.4 | 10.0 | 5.7 | 7.6 | 4.3 | 1.8 |

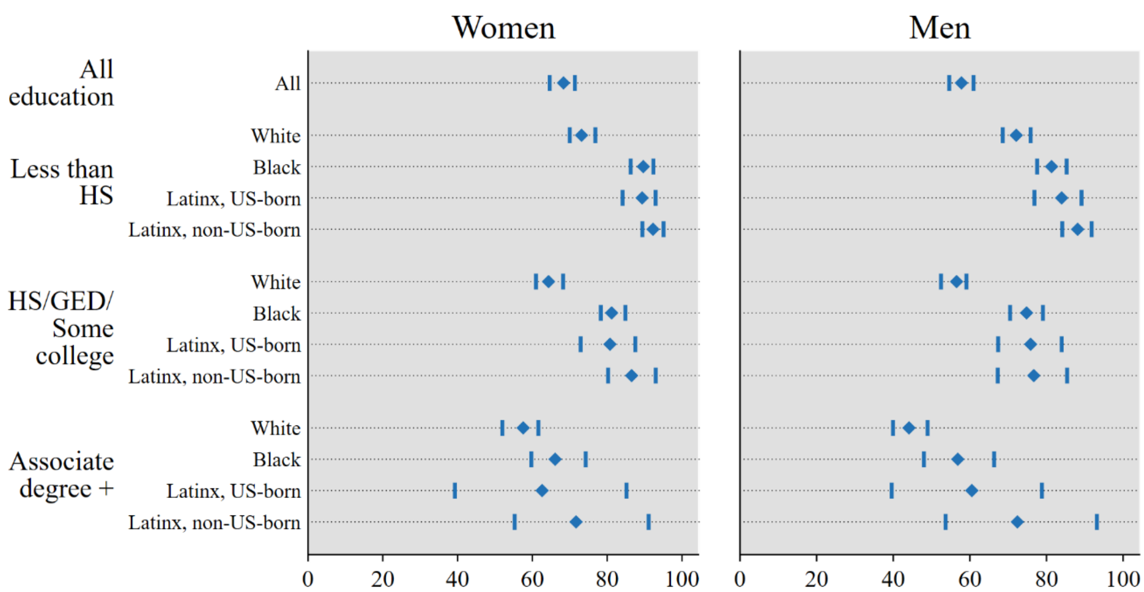
**Unconditional advantage or disadvantage**

| | Cumulative disadvantage | | | | Cumulative advantage | | | |
|---|---|---|---|---|---|---|---|---|
| | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born |
| Women | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | D | . | . | A | . |
| Postponed dementia onset, years | . | D | D | D | . | A | A | A |
| Add. dementia-free years | . | D | D | D | . | A | A | A |
| Increase in dem-free. % of life | . | D | D | D | . | . | A | A |
| Men | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | D | . | . | . | A |
| Postponed dementia onset, years | . | D | D | D | . | A | A | A |
| Add. dementia-free years | . | D | D | D | . | A | A | A |
| Increase in dem.-free % of life | . | D | D | D | . | . | A | A |

# D. Confidence Intervals

Figures in this section show 95% confidence intervals for various measures at age 50 by gender, race/ethnicity, nativity, and education. The confidence intervals are calculated as potentially asymmetric percentile intervals and are based on 500 bootstrap replications.

Panel A: Any Cognitive Impairment




Panel B: Dementia

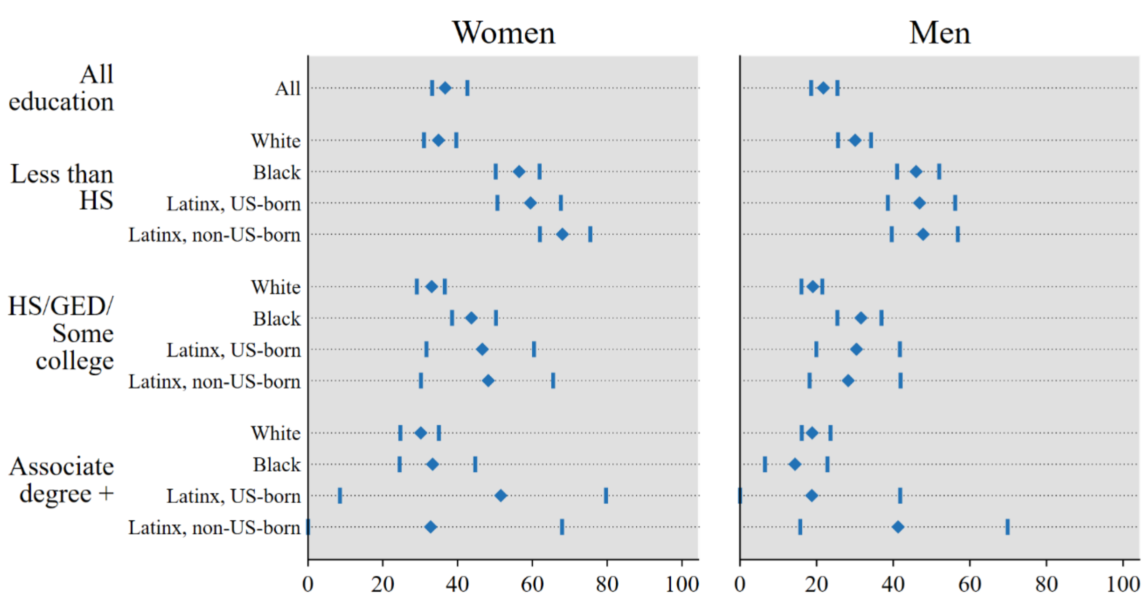
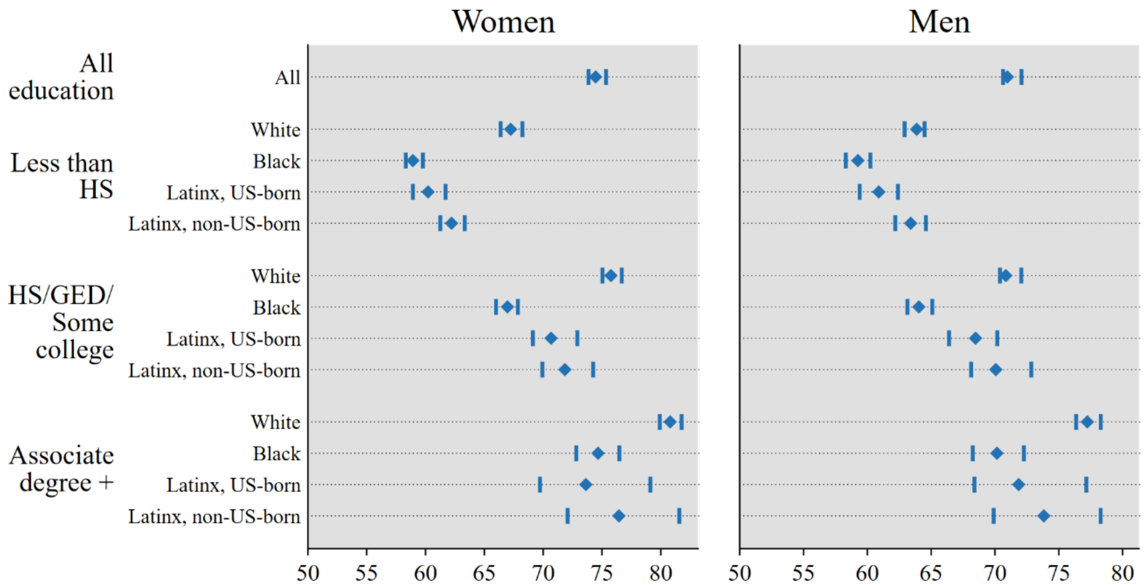



Fig. A1 Lifetime risk

Panel A: Any Cognitive Impairment




Panel B: Dementia

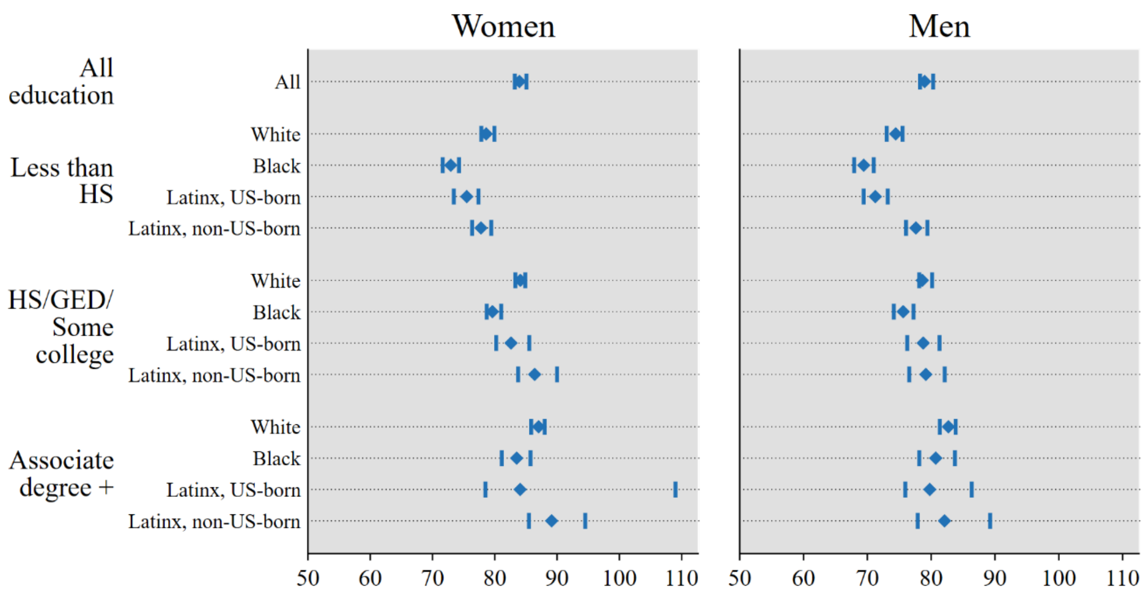
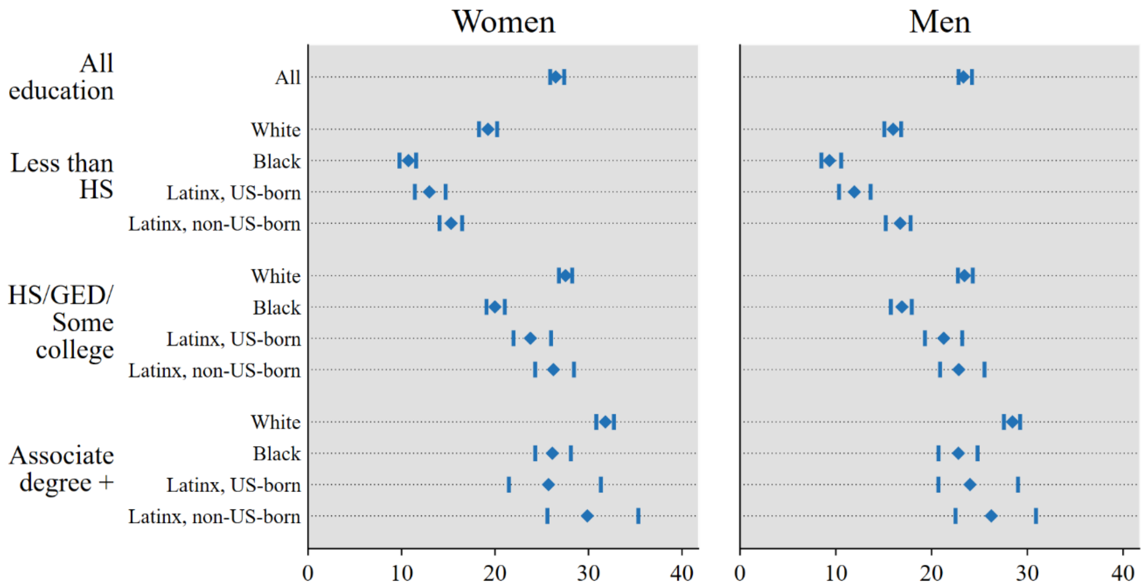



Fig. A2 Mean age at first cognitive impairment

Panel A: No Impairment




Panel B: Cognitive Impairment No Dementia

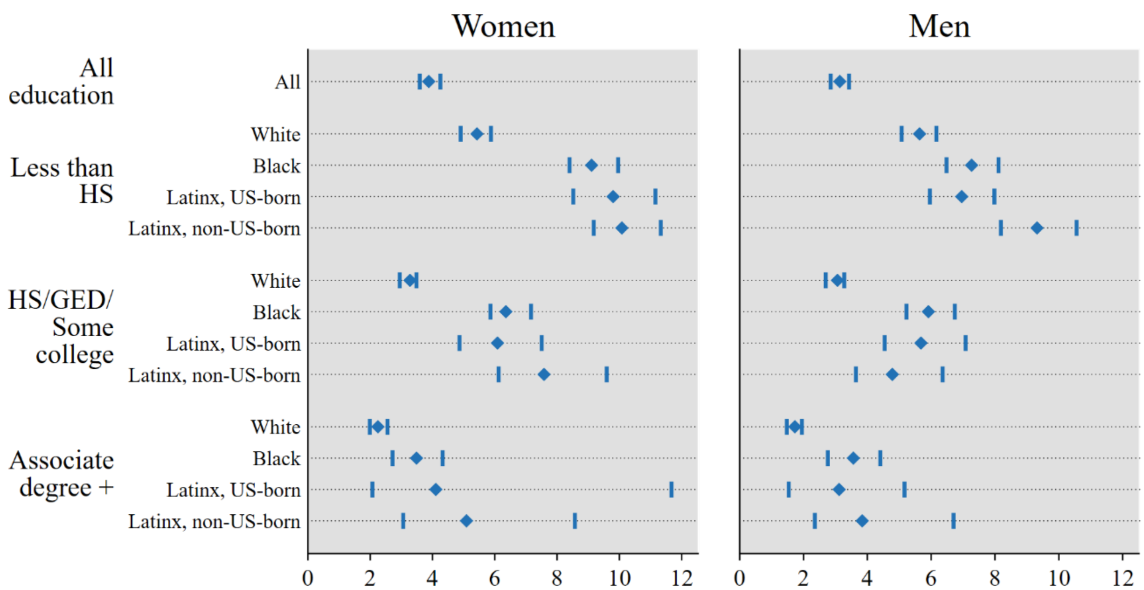
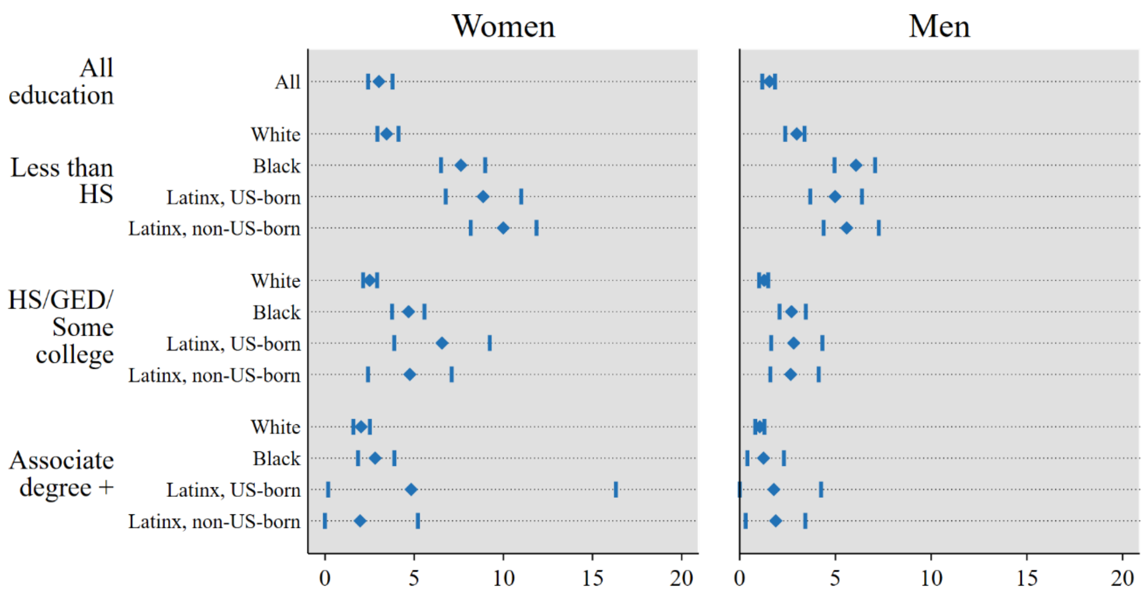



Fig. A3 Non-impaired (Panel A), cognitive impairment no dementia (Panel B), dementia (Panel C, next page), and total life expectancy (Panel D, next page)

Panel C: Dementia




Panel D: Total

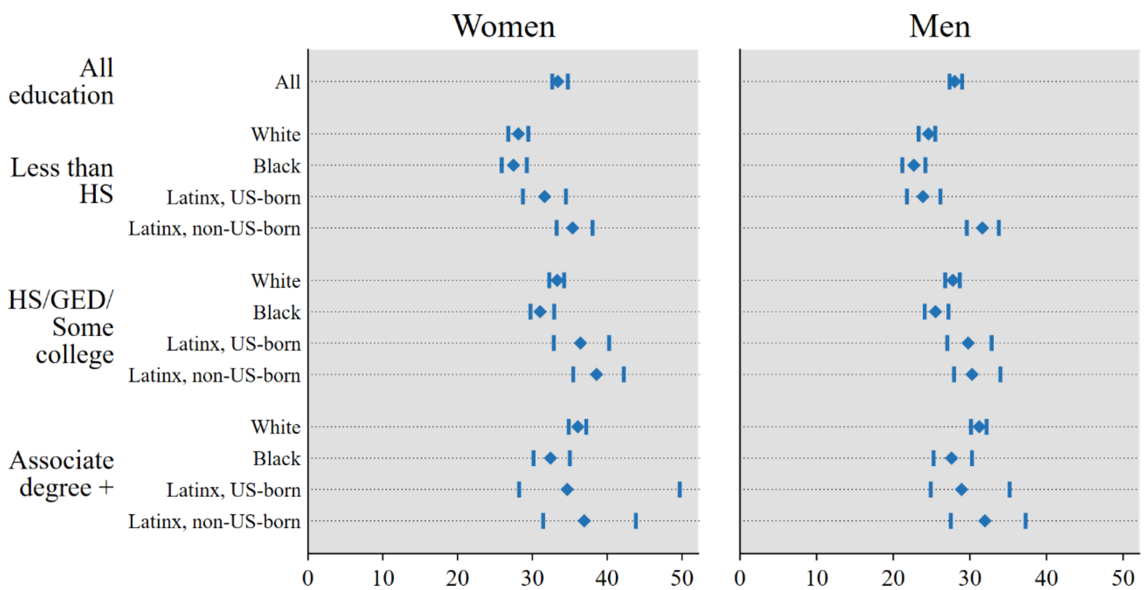



Fig. A3 (continued)

# E. Calculation of Outcome Measures Based on Simulated Life Histories

In this appendix section we lay out how we address potential measurement error in cognitive function scores. That Telephone Interview for Cognitive Status (TICS) scores are only an approximate measure of dementia can readily be seen from the fact that in the observed life histories subjects frequently leave the state of "dementia" to lower impairment states, which is at odds with the typical progression of dementia. That questionable vacillation of states is likely to be due to idiosyncratic, vanishing factors that affect performance on the interview day, like other ill health or a particularly stressful (or particularly elating) life situation. For our purposes, we can label these ephemeral factors "measurement error". Under the assumption of random measurement error, no difficulties arise for the calculation of state expectancies, as negative and positive errors cancel out over the entire sample. It is, however, problematic for the other two key outcome measures of the paper. With a fixed threshold of impairment as we use it in the paper and subjects generally being above that threshold at younger ages, measurement error, even if random, biases the mean age at first incidence downward and the lifetime risk upwards.

To counter this bias, we apply refined definitions of both CIND and dementia onset. Two CIND observations or two dementia observations that are adjacent are less likely to be caused by measurement error, so we use that criterion for onset of either impairment category. We ignore isolated observations of CIND and dementia. We allow for recovery from CIND but not for recovery from dementia. We complement these definitions by the following to account for special sequences: a) A single impairment observation (CIND or dementia) followed by death is counted as impairment, given that it is the first impairment observation in the life history. b) In a similar vein, if dementia onset is preceded by an isolated CIND observation, that observation counts as CIND. c) If a CIND observation is followed by dementia, or vice versa, and these two observations are embedded within observations without impairment, CIND is assumed for them.

Given this likelihood of measurement error, the standard sequential steps of multistate analysis seem to imply to 1) modify the observed life histories according to the rules above and then 2) use them for estimating the multinomial logistic models, which 3) in turn serve as the basis for transition probabilities upon which 4) analytical formulas for the final outcome measures are applied. Unfortunately, the first step of this procedure is not possible: The impairment onset rules cannot directly be applied to the observed life histories since many of them are censored, most notably at the end of our sample in 2018. For these subjects, an unambiguous (re-)classification of the last observation is not possible. As a remedy, we turn to a popular technique in multistate analysis and use the predicted transition probabilities based on the unmodified life histories to simulate completed life histories. Generally, if the number of simulated histories is large, then very simple calculations on them yield identical results to the application of analytical formulas. State and overall life expectancies are simply obtained as the average length of stay in the relevant state(s) across all simulated trajectories. Similar trivial averaging of numbers or counting of occurrences leads to results for mean age at first impairment and lifetime risk. In our analysis, however, we first reclassify states according to the two-period onset rules laid out above before we average simulated numbers or count simulated occurrences. Since the simulated life histories are complete (i.e., end in death), we can apply the two-period onset definitions without ambiguity. After this adjustment for measurement error, the counting and averaging results that are based on the modified simulated life histories are different from the analytical ones that are based on the original life histories. Exception to this is the overall life expectancy, whose estimate remains identical for both methods of calculation.

To obtain a measure of uncertainty, we use the bootstrap technique. Each bootstrap replication, which is based on a random draw of individuals from the sample, comprises all analytical steps, i.e., multinomial logistic estimation, prediction of transition probabilities, simulation of life histories, modification of the simulated life histories, and final outcome calculations. We base results on 100,000 simulated life histories and 500 bootstrap replications.

## TABLES

Table 1 Definitions, calculations, and decision rules for cumulative (dis)advantage (positive outcome measures[a])

| | Levels of the outcome | | Population fractions | |
|---|---|---|---|---|
| | Education | | Education | |
| Race/Ethnicity | Low | High | Low | High |
| Black | A | B | a | b |
| White | C | D | c | d |

**Assumptions for a positive outcome** (e.g., age at first impairment; higher values are beneficial):
A<C, B<D : within education levels, Blacks have lower levels of the beneficial outcome
B>A, D>C : within race/ethnicity, higher education leads to higher levels of the beneficial outcome

| | Educational differences | | | | | |
|---|---|---|---|---|---|---|
| | Absolute scale | | Relative scale | | Probability weighted (abs. scale) | |
| Race/Ethnicity | Loss from low educ. | Gain from high educ. | Loss from low educ. | Gain from high educ. | Loss from low educ. | Gain from high educ. |
| Black | A-B | B-A | A/B | B/A | a/(a+b) * (A-B) | b/(a+b) * (B-A) |
| White | C-D | D-C | C/D | D/C | c/(c+d) * (C-D) | d/(c+d) * (D-C) |
| Range of values | <0 | >0 | <1 | >1 | <0 | >0 |

**Decision rules, conditional[b] definition, absolute scale:**
Cumulative disadvantage: A-B < C-D (Blacks lose more from low education)
Cumulative advantage: B-A < D-C (Whites gain more from high education)

**Decision rules, conditional[b] definition, relative scale:**
Cumulative disadvantage: A/B < C/D (Blacks lose proportionally more from low education)
Cumulative advantage: B/A < D/C (Whites gain proportionally more from high education)

**Decision rules, unconditional definition, absolute scale:**
Unconditional cumulative disadvantage: a/(a+b)*(A-B) < c/(c+d)*(C-D) (Blacks lose more from low education)
Unconditional cumulative advantage: b/(a+b)*(B-A) < d/(c+d)*(D-C) (Whites gain more from high education)

**Relationships among the different definitions:**
Conditional absolute disadvantage implies conditional relative disadvantage, but not vice versa.
Conditional relative advantage implies conditional absolute advantage, but not vice versa.
There is no relationship between conditional results and unconditional results.

[a]Appendix A illustrates the definitions with numbers inserted for A-D and a-d. Appendix B states definitions, calculations, and decision rules for negative outcomes.

[b]Conditional on educational outcomes

Table 2 Descriptive characteristics of our analytical sample from the Health and Retirement Study by person-waves (1998-2018)

| | Overall sample | Distribution over cognitive states | | |
|---|---|---|---|---|
| | | NCI | CIND | Dementia |
| Person-Waves, total (%) | 191,503 (100%) | 143,944 (75%) | 33,121 (17%) | 14,438 (8%) |
| Age (years, mean) | 66.8 | 65.1 | 71.6 | 78.7 |
| Gender, % | | | | |
| Women | 52.9 | 79.8 | 13.9 | 6.3 |
| Men | 47.1 | 81.5 | 14.0 | 4.5 |
| Race/Ethnicity, % | | | | |
| White | 78.7 | 84.4 | 11.2 | 4.4 |
| Black | 10.1 | 62.7 | 26.2 | 11.1 |
| Latinx | 7.8 | 66.6 | 24.5 | 8.9 |
| Us-Born | 3.4 | 68.1 | 22.8 | 9.1 |
| Non-US-born | 4.4 | 65.4 | 25.9 | 8.7 |
| Educational Attainment, % | | | | |
| Less than high school | 17.1 | 51.1 | 32.6 | 16.3 |
| GED/H.S. Diploma/Some College | 51.6 | 82.7 | 13.1 | 4.2 |
| Associate/BA + | 31.3 | 93.2 | 5.2 | 1.6 |
| Childhood adversities (0-7), avg. | 1.8 | 1.7 | 2.3 | 2.3 |

All variables are different at the .05 level across the cognitive function states.
The number of respondents in the sample is 32,870. The tabulation excludes 12,297 deaths.

Wave-to-wave transitions, %

| | From: | | | |
|---|---|---|---|---|
| To: | Total | NCI | CIND | Dementia |
| NCI | 69.2 | 83.8 | 34.0 | 4.9 |
| CIND | 16.4 | 11.0 | 39.3 | 17.4 |
| Dementia | 7.2 | 1.4 | 15.2 | 46.7 |
| Death | 7.3 | 3.9 | 11.4 | 31.1 |
| Column Total | 100.0 | 100.0 | 100.0 | 100.0 |
| n of transitions | 169,257 | 127,065 | 29,287 | 12,905 |

Source: HRS (1998-2018). The waves are approximately two years apart and thus the transitions reflect two-year transitions.

Table 3 Conditional cumulative (dis)advantage: Panel A shows the benefit of higher education (Associates or higher vs. less than high school) in terms of either percentage point risk reduction (lifetime risk of any cognitive impairment and proportion cognitively impaired life) or delay in years (age at first cognitive impairment and years cognitively impaired) on both absolute and relative (percent change) scales. Panel B shows whether evidence in Panel A implies conditional cumulative advantage (A) for Whites or conditional cumulative disadvantage (D) for Blacks or Latinx, by nativity.

**Panel A**

| | Absolute (difference, pp* or years) | | | | Relative (% change) | | | |
|---|---|---|---|---|---|---|---|---|
| | White | Black | Latinx, US-born | Latinx, non-US-born | White | Black | Latinx, US-born | Latinx, non-US-born |
| **Women** | | | | | | | | |
| Reduced lifetime risk, pp. | 15.6 | 23.6 | 26.8 | 20.6 | 21.3 | 26.3 | 29.9 | 22.3 |
| Postponed impairment, years | 13.6 | 15.7 | 13.4 | 14.2 | 20.2 | 26.7 | 22.3 | 22.9 |
| Additional unimpaired years | 12.6 | 15.4 | 12.7 | 14.6 | 65.3 | 143.3 | 98.2 | 95.3 |
| Increase in unimp. % of life, pp. | 19.7 | 41.5 | 33.2 | 37.6 | 28.8 | 106.1 | 81.0 | 87.0 |
| **Men** | | | | | | | | |
| Reduced lifetime risk, pp. | 28.0 | 24.5 | 23.4 | 15.7 | 38.8 | 30.1 | 27.9 | 17.8 |
| Postponed impairment, years | 13.4 | 10.9 | 11.0 | 10.4 | 20.9 | 18.4 | 18.0 | 16.5 |
| Additional unimpaired years | 12.5 | 13.5 | 12.1 | 9.5 | 77.9 | 144.2 | 101.2 | 56.9 |
| Increase in unimp. % of life, pp. | 26.1 | 41.4 | 33.1 | 29.2 | 40.2 | 100.6 | 66.1 | 55.3 |

*pp: Percentage Point

**Panel B**

| | Absolute | | | | Relative | | | |
|---|---|---|---|---|---|---|---|---|
| | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born |
| **Women** | | | | | | | | |
| Reduced lifetime risk, pp. | . | D | D | D | . | D | D | D |
| Postponed impairment, years | . | D | A | D | . | D | D | D |
| Additional unimpaired years | . | D | D | D | . | D | D | D |
| Increase in unimp. % of life | . | D | D | D | . | D | D | D |
| **Men** | | | | | | | | |
| Reduced lifetime risk, pp. | . | A | A | A | . | A | A | A |
| Postponed impairment, years | . | A | A | A | . | A | A | A |
| Additional unimpaired years | . | D | A | A | . | D | D | A |
| Increase in unimp. % of life | . | D | D | D | . | D | D | D |

Table 4 Unconditional cumulative (dis)advantage: Panel A shows the probability-weighted benefit of higher education (Associates or higher vs. less than high school) in terms of either percentage point risk reduction (lifetime risk of any cognitive impairment and proportion cognitively impaired life) or delay in years (age at first cognitive impairment and years cognitively impaired). Panel B shows whether evidence in Panel A implies unconditional cumulative advantage (A) for Whites or unconditional cumulative disadvantage (D) for Blacks or Latinx, by nativity.

**Weighted (absolute) changes in outcomes**

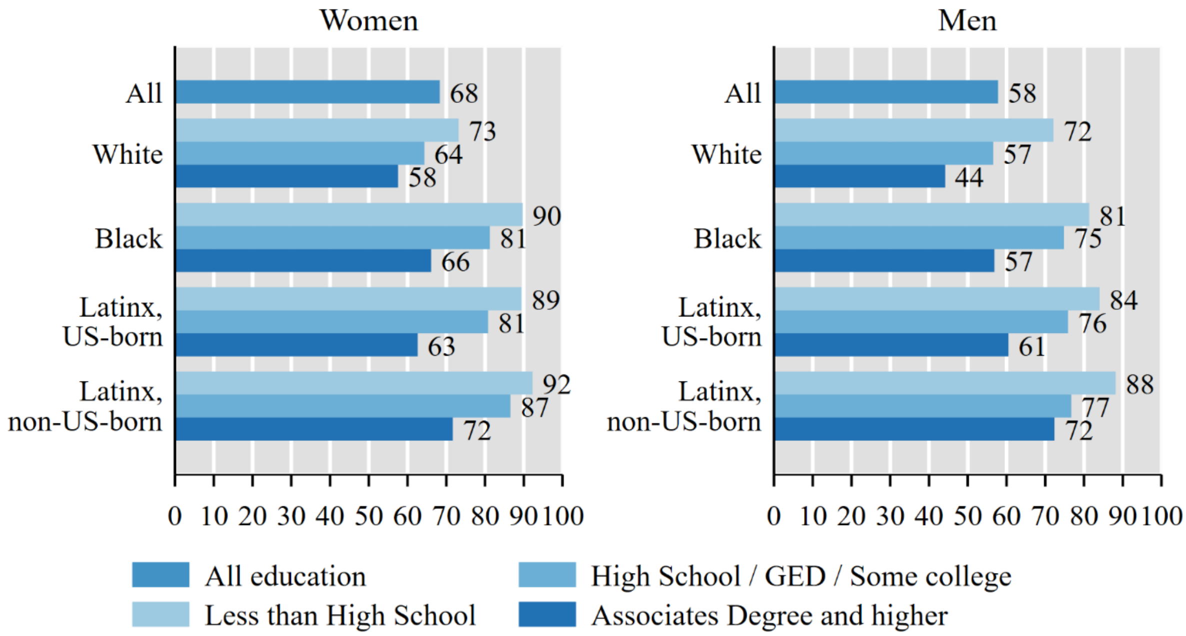
| | Weights: Low Educated | | | | Weights: High Educated | | | |
|---|---|---|---|---|---|---|---|---|
| | White | Black | Latinx, US-born | Latinx, non-US-born | White | Black | Latinx, US-born | Latinx, non-US-born |
| **Women** | | | | | | | | |
| Weights: Associates+ (Adv.) or <HS (Disadv.), % | 42.8 | 59.7 | 73.0 | 85.7 | 57.2 | 40.3 | 27.0 | 14.3 |
| Reduced lifetime risk, pp. | 6.7 | 14.1 | 19.6 | 17.6 | 8.9 | 9.5 | 7.2 | 3.0 |
| Postponed impairment, years | 5.8 | 9.4 | 9.8 | 12.2 | 7.8 | 6.3 | 3.6 | 2.0 |
| Additional unimpaired years | 5.4 | 9.2 | 9.3 | 12.5 | 7.2 | 6.2 | 3.4 | 2.1 |
| Increase in unimp. % of life, pp. | 8.4 | 24.8 | 24.2 | 32.2 | 11.3 | 16.7 | 9.0 | 5.4 |
| **Men** | | | | | | | | |
| Weights: Associates+ (Adv.) or <HS (Disadv.), % | 34.9 | 66.0 | 70.9 | 85.0 | 65.1 | 34.0 | 29.1 | 15.0 |
| Reduced lifetime risk, pp. | 9.8 | 16.2 | 16.6 | 13.4 | 18.2 | 8.3 | 6.8 | 2.3 |
| Postponed impairment, years | 4.7 | 7.2 | 7.8 | 8.8 | 8.7 | 3.7 | 3.2 | 1.6 |
| Additional unimpaired years | 4.4 | 8.9 | 8.6 | 8.1 | 8.1 | 4.6 | 3.5 | 1.4 |
| Increase in unimp. % of life, pp. | 9.1 | 27.3 | 23.5 | 24.8 | 17.0 | 14.1 | 9.6 | 4.4 |

**Unconditional advantage or disadvantage**

| | Cumulative disadvantage | | | | Cumulative advantage | | | |
|---|---|---|---|---|---|---|---|---|
| | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born | White (ref.) | Black | Latinx, US-born | Latinx, non-US-born |
| Women | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | D | . | . | A | A |
| Postponed impairment, years | . | D | D | D | . | A | A | A |
| Add. unimpaired years | . | D | D | D | . | A | A | A |
| Increase in unimp. % of life | . | D | D | D | . | . | A | A |
| Men | | | | | | | | |
| Reduced lifetime risk, % | . | D | D | D | . | A | A | A |
| Postponed impairment, years | . | D | D | D | . | A | A | A |
| Add. unimpaired years | . | D | D | D | . | A | A | A |
| Increase in unimp. % of life | . | D | D | D | . | A | A | A |

FIGURES

Panel A: Any cognitive impairment




Panel B: Dementia

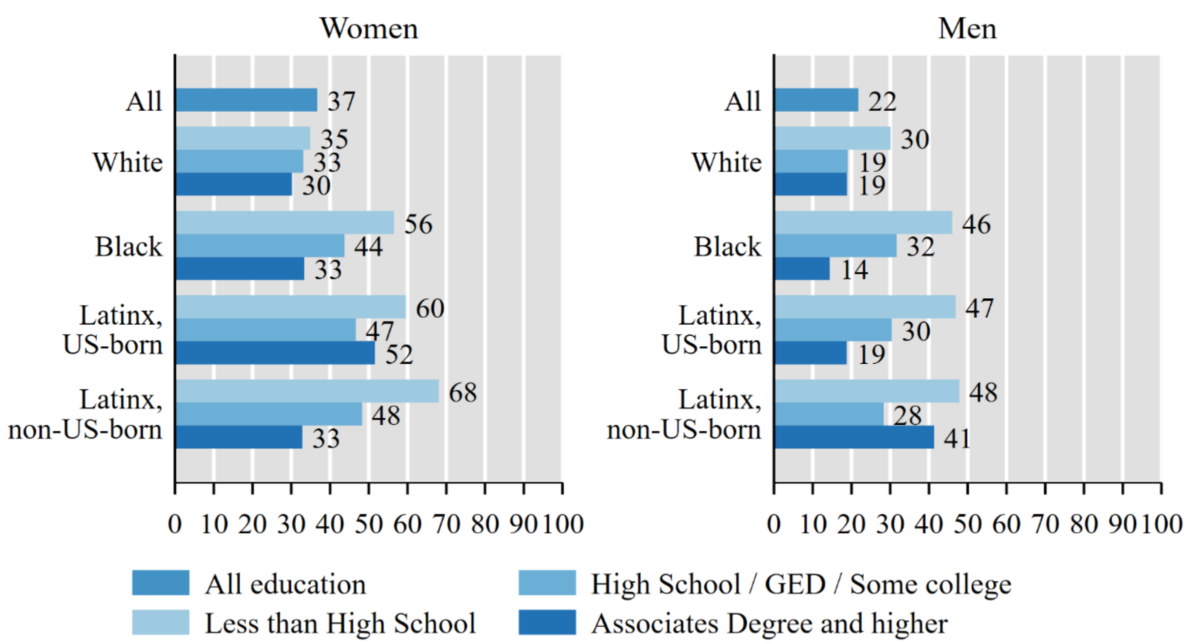
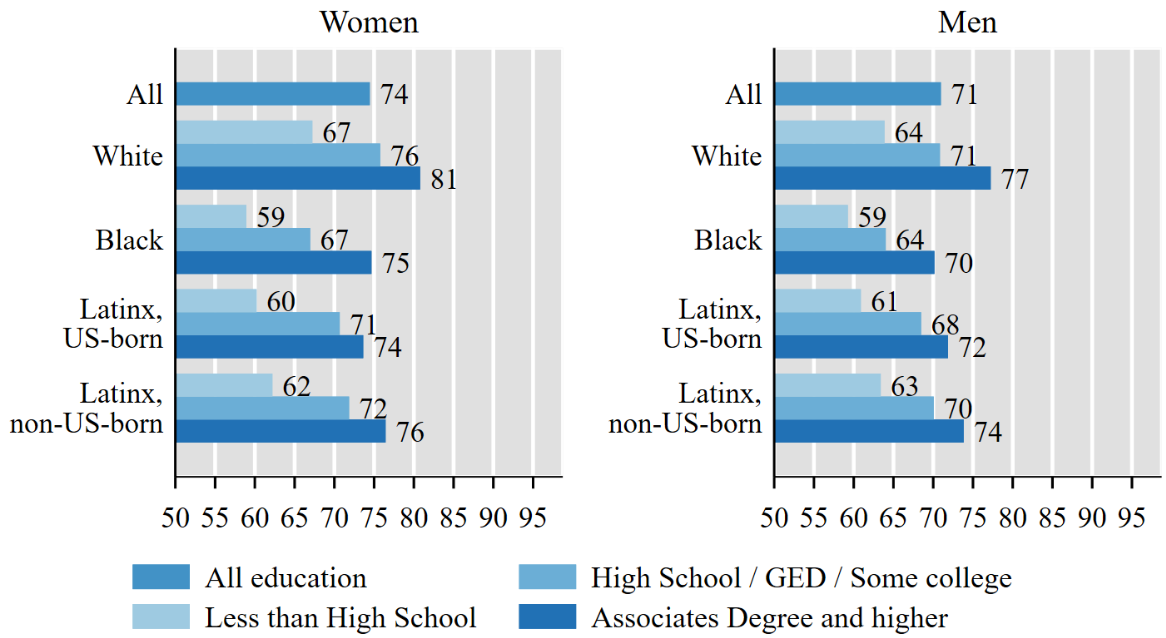



Fig. 1 Lifetime risk at age 50 of any cognitive impairment (Panel A) or dementia (Panel B) by gender, race/ethnicity, nativity, and education

Panel A: Any cognitive impairment




Panel B: Dementia

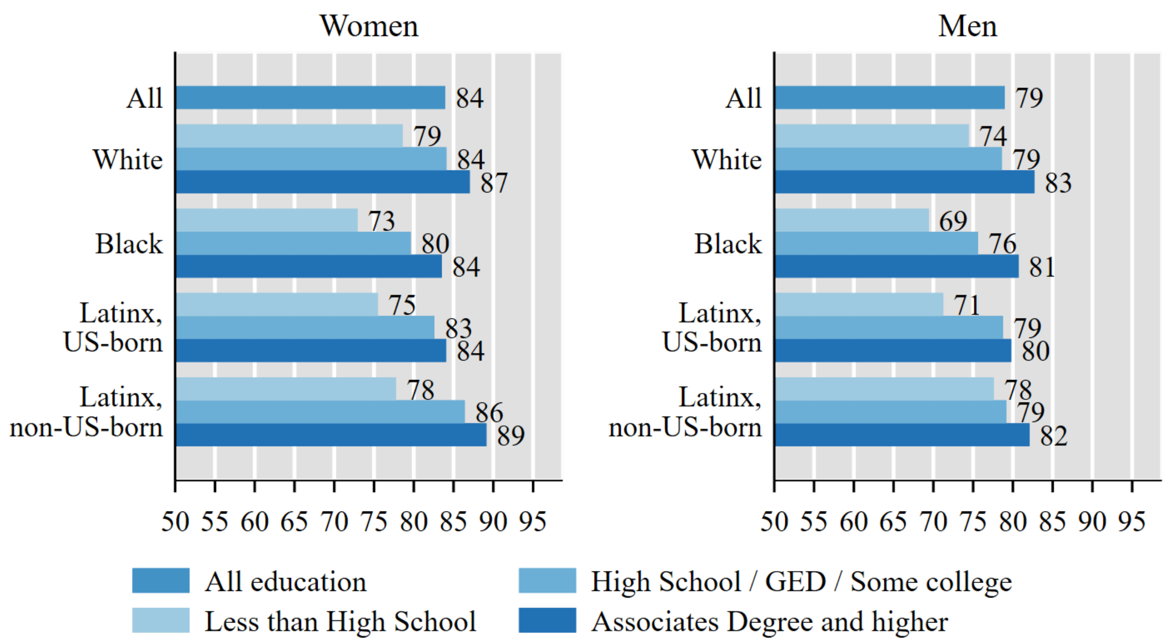
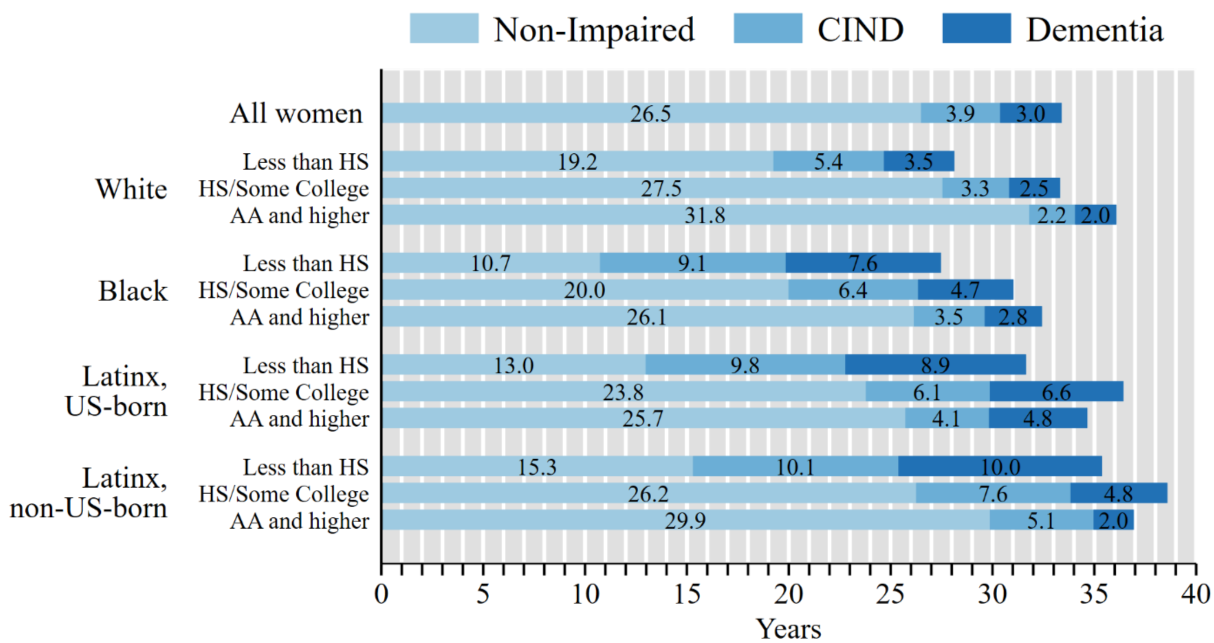



Fig. 2 Mean age at first incidence of any cognitive impairment (Panel A) or dementia (Panel B) by gender, race/ethnicity, nativity, and education

Panel A: Women




Panel B: Men

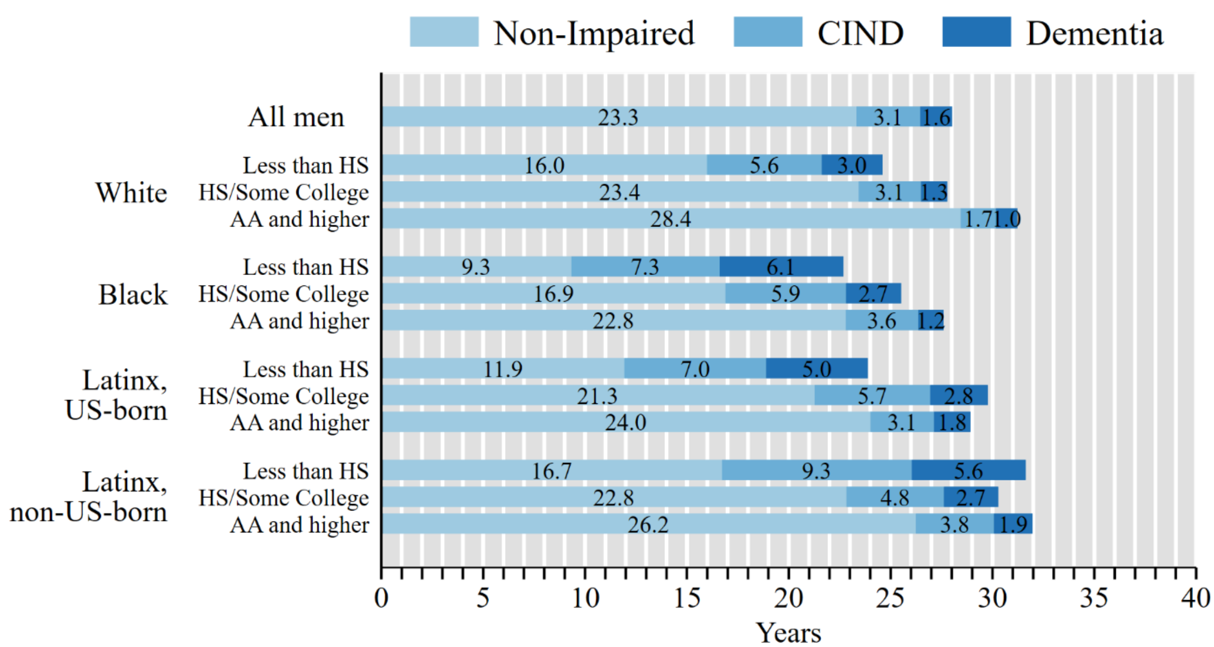
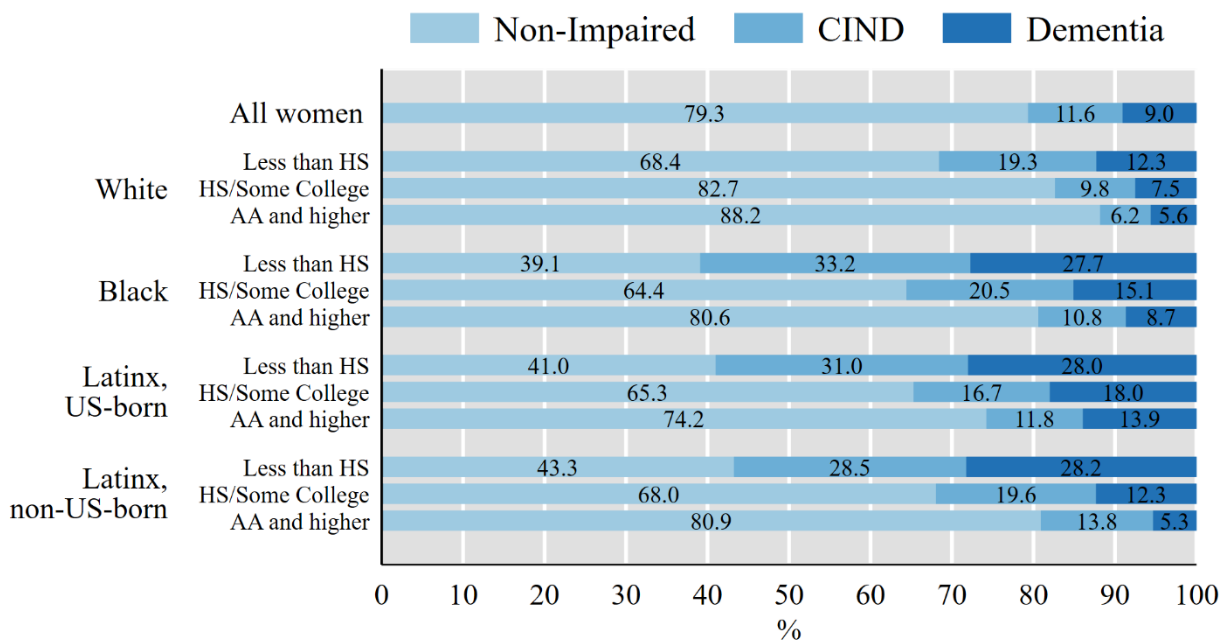



Fig. 3 Total, non-impaired, cognitive impairment no dementia, and dementia life expectancy at age 50 by gender, race/ethnicity, nativity, and education for women (Panel A) and men (Panel B)

Panel A: Women




Panel B: Men

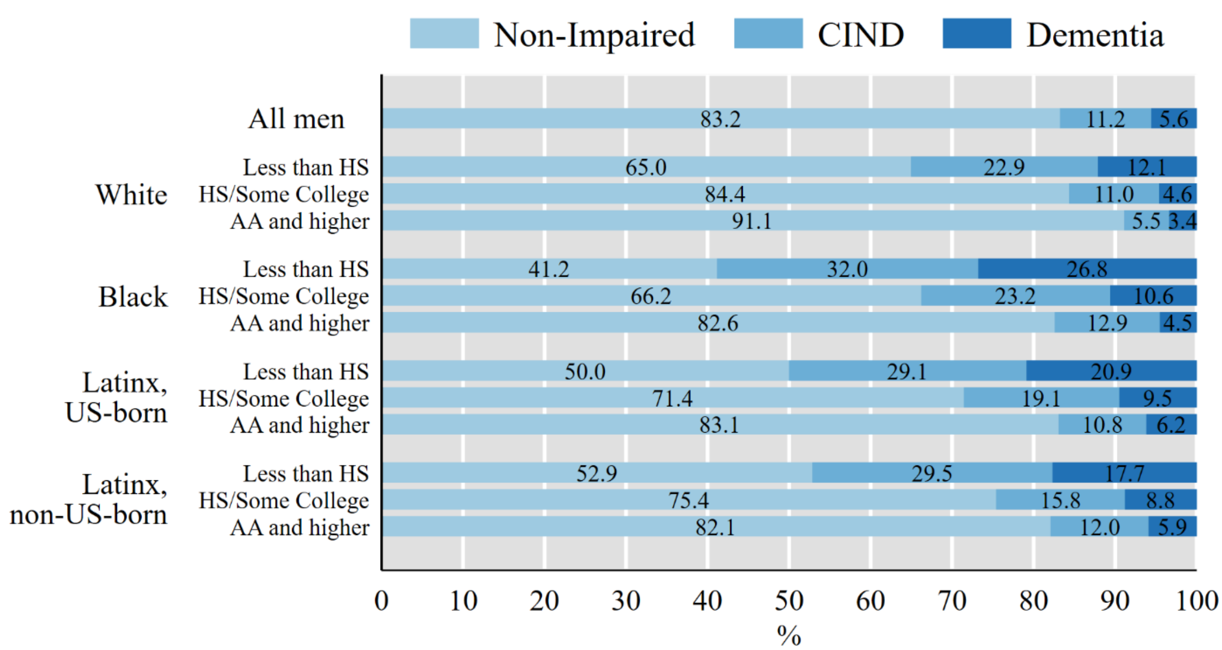
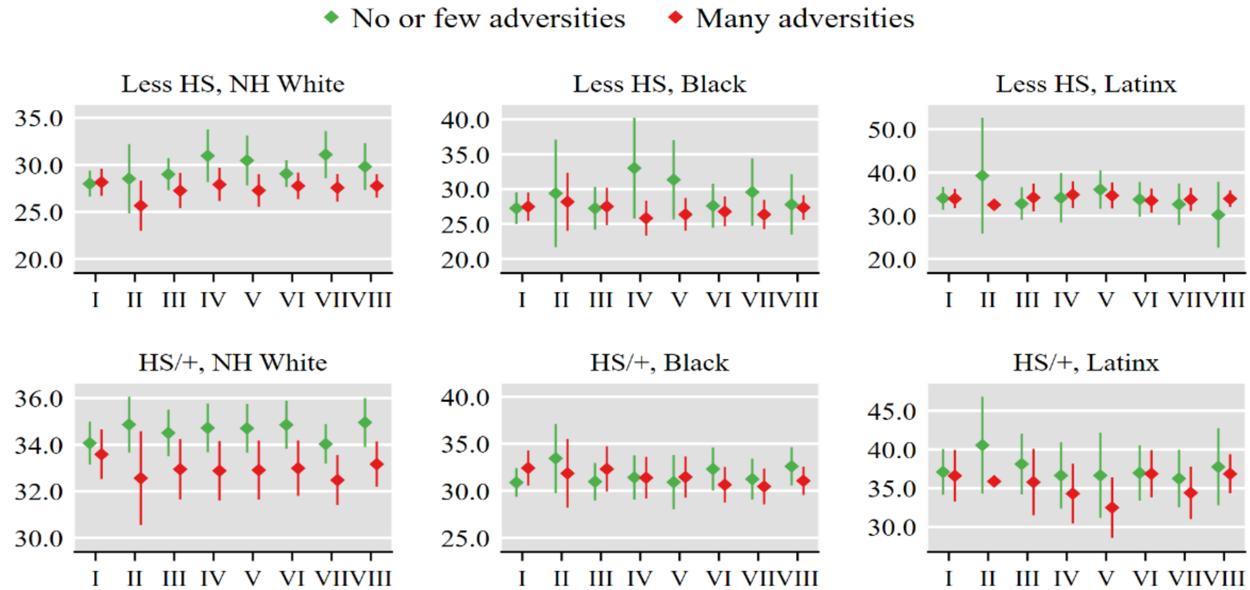



Fig. 4 Share of total life expectancy at age 50 spent in non-impaired, cognitive impairment no dementia, and dementia states by gender, race/ethnicity, nativity, and education for women (Panel A) and men (Panel B)

Panel A: Women




Panel B: Men

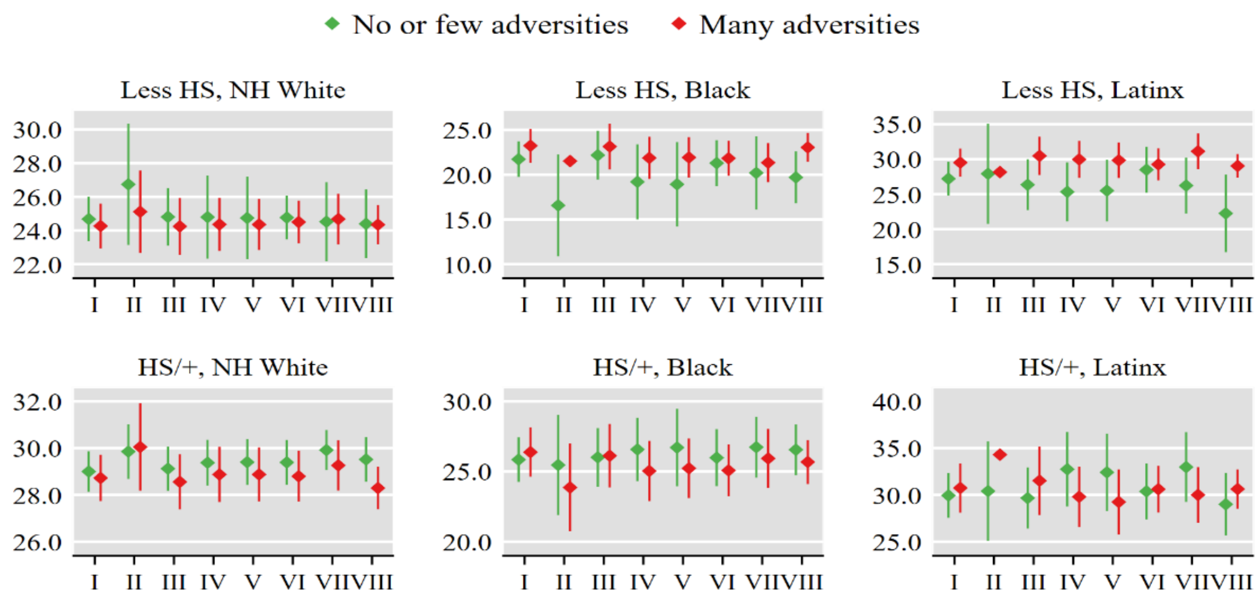
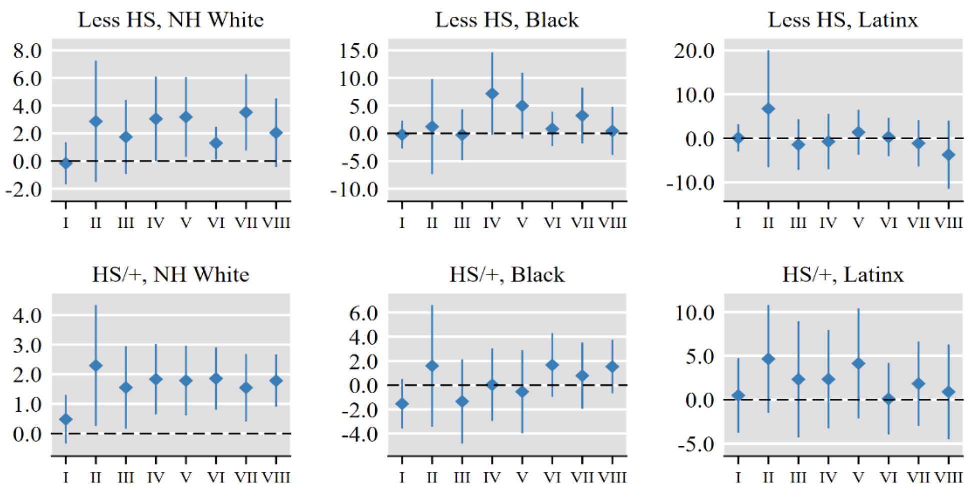



Fig. 5 Comparing various regression specifications' estimates for life expectancy for women (Panel A) and men (Panel B, next page) who experience low versus high childhood adversity levels.

Model specifications (I)-(VIII) for estimating the interaction effect of childhood adversities. Unless otherwise noted, all models use full four-way interactions of the dimensions of interest; education is binary only; and samples are split by gender. The measure of childhood adversity varies by the following:

- (I) 2 categories: 0-1 and 2+
- (II) 3 categories: 0, 1-4, and 5+
- (III) quasi-linear specification, each cell has intercept and slope
- (IV) 3 categories with a higher observation count in the tails
- (V) like (IV) but with 14 custom coefficient constraints applied to cells with a small n (≤5)
- (VI) like (IV) but with partial interactions only (gender-race-education and gender-race-adversity)
- (VII) like (IV) but based on a sample not split by gender and with all possible 3-way partial interactions only, omitting the 4-way one
- (VIII) 2 categories based on parent's education only

Panel A: Women




Panel B: Men

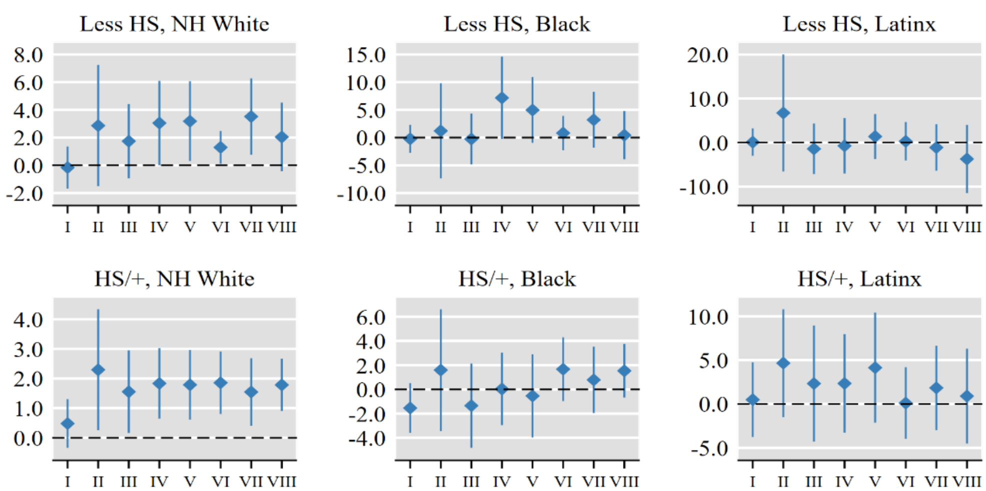



Fig. 6 Estimated difference by level of childhood adversity in women's (Panel A) and men's (Panel B) life expectancy across various regression specifications. Points above the dashed zero line indicate longer life expectancy for lower adversity, while points below indicate shorter life expectancy for lower adversity.

Model specifications are identical to the ones of Figure 5.