Social Science & Medicine 368 (2025) 117798



Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed





20-Year income volatility and cognitive function in the National Longitudinal Survey of Youth (1979) cohort: A replication and extension of CARDIA findings

Katrina L. Kezios [a,*], Calvin L. Colvin [a], Leslie Grasset [b], Catherine dP. Duarte [c], M. Maria Glymour [d], Adina Zeki Al Hazzouri [a]

[a] Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, NY, USA
[b] University of Bordeaux, Inserm, Bordeaux Population Health Research Center, UMR 1219, CIC1401-EC, Bordeaux, France
[c] Department of Epidemiology & Population Health, Stanford University School of Medicine, Stanford, CA, USA
[d] Department of Epidemiology, Boston University School of Public Health, Boston, MA, USA

ARTICLE INFO

Handling Editor: Social Epidemiology Office

Keywords:
Income
Income volatility
Cognition
Scarcity hypothesis
Replication

ABSTRACT

Grasset et al. previously reported that income volatility throughout early-to-mid adulthood (occurring during 1990–2010) in the CARDIA cohort was associated with worse midlife cognitive function. However, CARDIA lacked earlier-life cognition data, a major potential confounder. We replicate and extend this study in the National Longitudinal Survey of Youth (1979), which collected cognition measures in approximate adolescence. Following Grasset, we estimated associations between 20-year income volatility throughout early-to-mid adulthood (mean ages 27–47 in 1990–2010) and midlife cognitive function using confounder-adjusted linear regression models. Income volatility was assessed as the standard deviation (SD) of the percent change in income between successive annual or biennial surveys and as the number of income drops >25% between surveys. For cognition, we averaged z-scores on immediate and delayed 10-word recall, backwards counting, and serial 7's tasks. We found that income volatility and number of income drops were negatively associated with midlife cognitive function (*e.g.,* each SD increase in income volatility was associated with 0.081 SD lower cognition z-scores, 95% CI: −0.121, −0.041) independent of earlier-life cognitive skills (*e.g.,* before adjustment, $\widehat{\beta}$ = -0.095, 95% CI: −0.136, −0.054). Our study adds to a growing literature suggesting life course financial volatility may adversely impact cognitive aging.

1. Introduction

Prior studies have demonstrated strong associations between sustained low income and adult cognitive outcomes (Lynch et al., 1997; Lyu and Burr, 2016; Marden et al., 2017; Turrell et al., 2002; Wang et al., 2023; Zeki Al Hazzouri et al., 2017). However, the potential cognitive impacts of income volatility–or, unpredictable income fluctuations over time–are less well examined (Grasset et al., 2019). Income volatility may harm long-term brain health over and above the influence of average income level. The unpredictability of income fluctuations is a major cause of stress and anxiety (American Psychological Association, 2023; Basu, 2017; Blair and Raver, 2016; Dickler J, 2017; The Pew Charitable Trusts, 2017; Wolfe, 2022), which are both associated with cognitive function and/or decline (Blair and Raver, 2016; Chen et al., 2022; Kulshreshtha et al., 2023; McEwen and Rasgon, 2018). Ongoing worry and mental preoccupation about precarious financial situations may result in cognitive burden or overload (Appelhans, 2023; Gennetian and Shafir, 2015; Mani et al., 2013; Mullainathan and Shafir, 2013; Sayre, 2023), particularly for individuals with limited resources to absorb income shocks or manage finances during periods of substantial volatility (Appelhans, 2023; Gennetian LA & Hardy B, 2023; Morduch and Schneider, 2017; The Expanding Prosperity Impact Collaborative, 2016). Compounding the issue, income volatility itself hinders capacity to plan finances and accrue resources to help cushion periods of instability (Dickler J, 2017; Gennetian LA & Hardy B, 2023; Prause et al., 2009). Consequently, the cognitive overwhelm individuals may feel due to income volatility, especially if experienced alongside scarcity, may impede cognitive function and compromise investments in other

* Corresponding author. 722 W. 168th Street, Room 504, New York, New York, 10032, USA.
E-mail address: klk2131@cumc.columbia.edu (K.L. Kezios).

https://doi.org/10.1016/j.socscimed.2025.117798
Received 28 June 2024; Received in revised form 27 January 2025; Accepted 30 January 2025
Available online 1 February 2025
0277-9536/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

health-promoting resources or behaviors that are beneficial for brain health (Mullainathan and Shafir, 2013). Income volatility has increased over time in the US (Addo and Servon, 2022; Duncan, 1996; Dynan et al., 2012; Gottschalk and Moffitt, 2009; Gottschalk et al., 1994; Hardy and Ziliak, 2014; Jacobs E & Hacker J, 2008), and the majority of Americans now live paycheck-to-paycheck in situations of limited financial security (American Psychological Association, 2023; Bennett R, 2023; Dickler J, 2023; Morabito C, 2023), making income volatility–and its potential policy solutions–a pressing public health concern. It is therefore critical to improve understanding of the health consequences of income volatility, especially among those most financially marginalized (Basu, 2017).

In a 2019 paper, Grasset et al. evaluated the long-term relationship between income volatility and cognitive outcomes using data from the Coronary Artery Risk Development in Young Adults (CARDIA) Study. They observed that higher volatility and experiencing ≥2 substantial income drops over a 20-year period in early-to-mid adulthood were associated with poorer performance on midlife cognitive assessments (Grasset et al., 2019). However, their study had two key limitations: 1) possible lack of generalizability, due to the selected CARDIA sample and 2) potential residual confounding given no assessments of baseline cognition in CARDIA. It is important to assess whether Grasset et al.'s findings replicate when these challenges can be overcome. The National Longitudinal Survey of Youth (1979) (NLSY79) enables replication and extension of these findings in a nationally representative sample which prospectively collected measures of adolescent/early adulthood cognition. Specifically, NLSY79 and CARDIA include participants of the same birth cohorts, collect data over a similar time frame, and evaluate cognition in midlife (albeit, using different cognitive batteries). The collection of earlier-life cognition information in NLSY79 enables adjustment for this potential confounder.

Thus, using NLSY79 data, we first replicate Grasset et al.'s findings. Then, because the health effects of income volatility may be exacerbated in the presence of scarcity, we extend their findings by exploring various indicators of structural marginalization (experiences of which constrain resources and opportunities) and financial resources as modifiers of the relationship between early-to-middle adulthood income volatility and midlife cognitive function. These findings will help advance understanding of the context in which income volatility may be particularly harmful for cognitive health.

2. Methods

2.1. Study design and sample

The NLSY79 is an ongoing cohort study of 12,686 men and women initiated in 1979 by enrolling US residents aged 14–22 (born 1957–1964) (Rothstein et al., 2019). This cohort was composed of three independent probability samples, some of which (*e.g.,* oversamples) were later discontinued. Following Grasset et al., 2019 (hereafter, "Grasset"), we defined our exposure period from 1990 to 2010; participants were 25–33 years old in 1990 in our NLSY79 sample vs. 23–35 in CARDIA. Supplemental Table S1 presents a complete comparison of study design, sample, and analysis features between studies. NLSY79 surveys occurred annually from 1990 to 1994 and every 2 years from 1994 to 2010, for 13 survey waves from 1990 to 2010. Detailed below (and summarized in Fig. 1), for this analysis, our sample included individuals who remained under observation in 1990 and were not part of a later excluded oversampled group, had at least three income measures over the exposure period (including at baseline), participated in NLSY79's cognition module in 2010–2016, and had complete data on all study variables, including all cognitive assessments (N = 2643).

2.2. Exposure: Income volatility from 1990 to 2010

At each survey, pre-tax income for the previous calendar year was

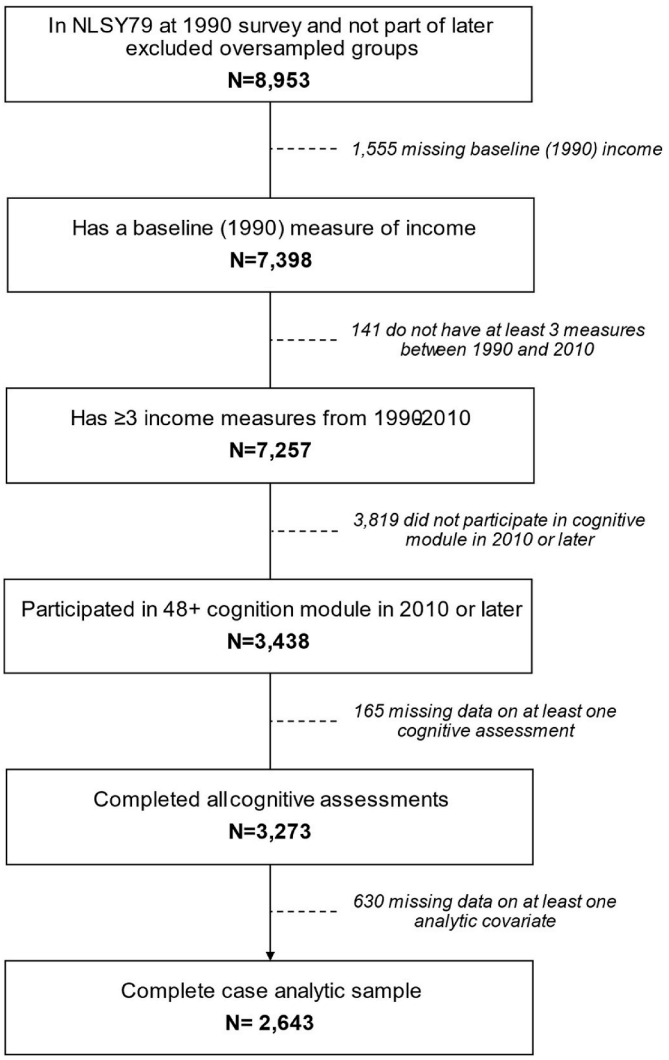


Fig. 1. Selection into analytic sample from starting pool of eligible participants in the National Longitudinal Survey of Youth (1979) cohort.

self-reported in nominal dollars from numerous sources (*e.g.,* wage/salary, military income, government/non-government transfers) for each respondent and for all related household members. Net family income was created by NLSY79 by summing income from all sources, with income values in the top 2% recoded as the group average of that top range. We limited analyses to participants with a measure of income at baseline (1990) and at least 2 additional income measures by 2010 (N = 7,257, Fig. 1). Using this sample, we created two measures of income volatility, consistent with Grasset: (i) the intraindividual standard deviation (SD) of the percent change in income between survey years from 1990 to 2010, and (ii) the number of substantial income drops between survey years from 1990 to 2010.

SD of the percent change in income: We deflated income measures to real 1990 dollars using the consumer price index for each corresponding year (Federal Reserve Bank of Minneapolis) and equivalized all income measures for household size by dividing by the square-root of the number of household members (Reeves RV & Pulliam C., 2019). Then, for each participant, we calculated the percent change in inflation-adjusted equivalized income between each consecutive survey as follows:

$$\left[\frac{Y_{t_2} - Y_{t_1}}{0.5(Y_{t_1} + Y_{t_2})}\right] * 100$$

where Y indicates a participant's income measure and t indicates a given time point (Elfassy et al., 2019; Grasset et al., 2019). This way of calculating percent change is common in economic applications (Dahl et al., 2011; Dynan et al., 2012; Ziliak et al., 2011), and compared with alternative approaches it has the advantage of being less sensitive to extreme income swings, symmetric with respect to increases and decreases, and naturally bounded by −200% and 200% (Dynan et al., 2012; Grasset et al., 2019). Finally, for each participant, we compute the SD of their percent changes across time. This measure captures the magnitude of income volatility over time but does not distinguish negative from positive income changes; however, instability regardless of direction has been conceptualized as a financial stressor. Higher values indicate higher volatility.

Number of income drops >25%: For each participant, we counted the number of times over the exposure period their income reported on a survey was >25% less than their income reported on the prior survey and less than their average income from 1990 to 2010. A 25% threshold is commonly used to capture substantial income drops (Elfassy et al., 2019; Grasset et al., 2019; Liu and Cheng, 2023; Morduch and Schneider, 2017; The Pew Charitable Trusts, 2017). Number of income drops could theoretically range from 0 to 12 and was categorized as 0, 1, 2, or 3+ drops. Consistent with Grasset and others (Elfassy et al., 2019), because inflation alone could cause a 25% income drop for some income levels but not others, we did not adjust this measure for inflation. This measure focuses on negative income changes over time, which may be even worse for health than experiencing just income spikes or a combination of income gains and drops.

Missing income data: To account for exposure trajectories of varying lengths, participants were assigned a value for the number of non-missing income observations out of 13 possible time points; 81% of the sample completed income information at ≥10 time points. In calculating the volatility measures, we used successive measures, disregarding intervening waves with missing data. This approach has the advantage of making no assumptions about income stability/volatility between time points. In a sensitivity analysis, missing income measures were carried forward, consistent with Grasset. Because this approach carries the same value forward between time points, it spuriously reduces the volatility of the income trajectory, producing a conservative estimate of exposure. However, both the "carry forward" and "use next available measure" approaches produce the same number of income drops for each individual.

2.3. Outcome: Cognitive assessments

From 2006 to 2016, NLSY79 participants were administered a Cognitive Module during the survey year in which they turned at least 48 (Rothstein et al., 2019). Participants completed a modified version of the Telephone Interview for Cognitive Status (TICS-m) which included immediate and delayed 10-word recall, backwards counting, and serial 7's subtraction tasks. For all assessments, higher scores indicate better performance. Because 2010 was the end of our exposure period, we restricted the sample to individuals who completed their cognitive module from 2010 to 2016 (N = 3438). 3273 individuals completed all cognitive assessments (Fig. 1). We examined raw scores (for comparison with Grasset) and standardized scores (z-scores) for cognitive outcomes, and z-scores were calculated in the final complete case analytic sample (N = 2643).

Immediate recall: Participants were presented with a randomly assigned set of 10 words and immediately asked to recall as many words from that list as possible. Possible raw scores range from 0 correctly recalled words to 10; sample raws scores ranged from 1 to 10 and z-scores ranged from −3.08 to 2.24.

Delayed recall: Later in the module, participants were asked to recall the previously presented 10-word list, with possible scores again ranging from 0 to 10. Raw scores and z-scores in the analytic sample ranged from 0 to 10 and −2.46 to 2.31, respectively.

Backward counting: Participants completed two assessments, counting back from 20 and from 86 for 10 numbers. Participants scored 0 if they performed the task incorrectly, 1 if they performed the task correctly upon request for a second attempt, and 2 if they performed the task correctly on their first try. Since a second attempt was only given if requested, and few participants had a second-attempt score, we dichotomized scores as 1 if correct on the first attempt and 0 otherwise. We then averaged each participant's scores on both assessments and standardized them; for 20 participants with only one of the two assessments, their single assessment score was used. Z-scores ranged from −5.04 to 0.34.

Serial 7's subtraction: Participants were asked to subtract 7 from 100 and then to keep subtracting 7 from each result until the subtraction had been done five times. Each subtraction is evaluated independently so that one wrong response does not impact the remaining subtractions. The minimum possible score was 0 and the maximum 5, and z-scores ranged from −2.64 to 0.85.

Memory domain score: We created a memory domain raw score by summing participant scores for immediate and delayed word recall tests (sample min-max: 2–20), which aim to capture episodic memory (Runge et al., 2015). We created a standardized memory score by averaging the raw scores for immediate and delayed recall and then z-scoring this quantity; z-scores ranged from −2.66 to 2.46.

Attention domain score: Backward counting (aiming to capture executive function) and serial 7's (aiming to capture numeracy) tasks are collectively conceptualized as measures of attention (Carlew et al., 2020). We created an attention domain raw score by summing participant scores on the backward counting and serial 7's tasks (sample min-max: 0–7). We also created a standardized attention score by averaging the z-scored versions of these assessments, which gave them equal weight in the domain score; we then standardized this average score, and z-scores ranged from −5.63 to 0.70.

Modified TICS global cognition score: Following prior work (Cox and Wallace, 2022), we created a modified TICS summary cognition score (TICS-m) by summing raw scores on immediate and delayed recall, both backward counting, and serial 7s tasks (sample min-max: 4–27). We also created a TICS-m standardized score by averaging all standardized scores for individual cognitive assessments to give them equal weight in the overall score and then standardizing this average score so that it had a mean of 0 and SD of 1 in the analytic sample. TICS-m z-scores ranged from −5.00 to 2.04.

Cognitive impairment: Following prior work (Cox and Wallace, 2022), participants with TICS-m raw scores of 0–6 were classified as "dementia", 7–11 as "cognitive impairment (no dementia)", and 12–27 as "no cognitive impairment, no dementia". We created a binary "cognitive impairment" outcome variable using a cutoff of ≤11 to indicate cognitive impairment (vs. no cognitive impairment).

For comparison, in CARDIA, midlife cognition was assessed by the Rey Auditory Verbal Learning Test (RAVLT, min-max: 0–15) (Rosenberg et al., 1984), the Digit Symbol Substitution Test (DSST, min-max: 0–133) (Wechsler, 1997), and the Stroop test interference score (Stroop, timed test, no set min or max score) (Stroop, 1935). In Grasset, individual assessment raw scores were used as outcomes and a global measure of cognition was not examined.

2.4. Confounders

To replicate Grasset's analyses as closely as possible, we considered the following potential confounders (measured in 1990 unless otherwise specified): chronological age, interviewer-assessed gender (female, male), interviewer-assessed race and self-reported ethnicity (non-Hispanic Black, Hispanic, and non-Hispanic, non-Black), educational attainment in 1989 (≤12 years, >12 years), marital status (married, separated/divorced/widowed, never married), body mass index (BMI in kg/m^2 using self-reported weight in 1990 and self-reported height in 1985), smoking status in 1992 (current, former, never), depressive

symptoms in 1992 (measured using the Center for Epidemiologic Studies Depression Scale (CESD)-20, dichotomized at 16), health insurance type (employer-provided, other, none), drinking status in 1992 (heavy, light/moderate, none, using sex-specific guidelines from the Centers for Disease Control and Prevention), income (equivalized for household size), and employment status (works full-time, does not work full-time). Race and ethnicity, gender, and BMI were considered to, in part, capture differences in exposure to social marginalization that constrains earning potential and resource accumulation (*e.g.,* structural racism, structural sexism, size discrimination) (Homan, 2019; Mason, 2012; Lett et al., 2022). Health insurance type and drinking status were used as proxies for health markers unavailable at baseline in NLSY79 but controlled for in Grasset's analyses, such as antihypertensive medication use, total cholesterol, and physical activity (Biddinger et al., 2022; Gu et al., 2012; Wilper et al., 2009). Supplemental Table S1 provides a detailed comparison of confounders available in both studies, their measures, and key differences. Finally, different from Grasset, in all models we adjusted for percentile scores on the Armed Forces Qualification Test (AFQT, administered in 1980, when participants were aged 15–23, and renormed in 2006), which is suggested by some (Cameron and Heckman, 1993; Holz and Tienda, 1998) but not others (Cordero-Guzmán, 2001; Fischer et al., 2020) to measure cognitive skills.

Like Grasset, we also created summaries of time-varying confounders from 1990 to 2010, including: proportion of the exposure period participants were married, currently smoked, scored ≥16 on the CESD-20, had employer-provided health insurance, drank heavily, and worked full-time (all summarized as always vs. never/sometimes); we also computed participants' average BMI and average 1990 income (equivalized for household size) over the exposure period.

2.5. Modifiers

Extending Grasset's analysis, we also explored if income volatility's impact on cognition was worse for those with fewer socioeconomic resources, including structurally marginalized groups such as Black Americans, women, and the impoverished, who disproportionately experience socioeconomic disenfranchisement due to various forms of discrimination. For example, past exposure to racist and/or sexist labor market, housing market, or banking practices (among others) influences financial resources an individual or their social network members can access to cushion short term income fluctuations, and experiencing income volatility in the context of fewer resources could alter/amplify its consequences for cognition. Thus, we evaluated as modifiers race and ethnicity, gender, and their joint strata. We also examined modification by different aspects of socioeconomic status/resources summarized across the exposure period (1990–2010), including: poverty status (in poverty at least once, never), average wealth (<$2,000, ≥$2000), reporting savings of $2000 or more (always, sometimes, never), reporting owning a home (never, sometimes/always), educational attainment (≤12 years, >12 years), and income class both in 1990 and of the average income over the exposure period (low, middle, high (Pew Research Center, 2016)). For wealth and savings, $2000 was used because a lack of "rainy day" savings of $2000 is a common indicator of financial fragility in the US (Brobeck, 2008; Grinstein-Weiss et al., 2014; Lusardi et al., 2011; The Pew Charitable Trusts, 2015b; 2017). Complete details on financial modifiers and their operationalization are in the **Supplemental Methods**.

2.6. Statistical analyses

Following Grasset, we first described participants' characteristics at baseline (*e.g.,* means, frequencies) in the overall sample and within strata of number of income drops. We then used linear regression to estimate the effect of income volatility (per 1 SD difference) and number of income drops on midlife cognition (both raw and z-scores for global cognition and memory and attention subdomains) and logistic regression when the outcome was cognitive impairment. Model assumptions (*e.g.,* normality) seemed reasonably satisfied, and when model-based vs. bootstrapped 95% confidence intervals (CIs) were compared, results were nearly identical; therefore, we report model-based 95% CIs. For each analysis, models were progressively adjusted for potential confounders at baseline. Model 1 included earlier-life cognitive skills, age, gender, race and ethnicity, education, and marital status (besides earlier-life cognition, these adjustments were identical to those in Grasset's Model 1). Model 2 additionally included BMI, smoking status, depressive symptoms, health insurance status, and drinking status. Finally, Model 3 additionally included baseline income and employment status. Each model also adjusted for the number of income measures (out of 13) each participant contributed to the exposure period and the year in which they completed their age 48+ cognition module. To assess effect modification, we compared stratum-specific associations between continuous income volatility and midlife cognition and used Omnibus F-tests to test for significant additive interactions ($p_{int}<0.05$) comparing models with and without cross-product terms between income volatility and modifiers. All analyses were conducted using R version 4.1.0.

2.7. Sensitivity analyses

To see if results were driven by a particular cognitive assessment, we repeated analyses using individual assessment raw and z-scores as outcomes. We also repeated main analyses using the alternative imputation strategy for income volatility (carry forward). For both exposures, we repeated main analyses adjusting for summaries of time-varying covariates vs. their baseline values. To enhance generalizability to other income volatility literature, we examined two alternative exposures not examined in Grasset: residual income volatility (Cheng, 2014; Liu and Cheng, 2023) and the percent of income drops experienced across time (details in **Supplemental Methods**). Finally, health shocks or chronic health conditions experienced over the exposure period could cause income shocks and affect midlife cognition; attempting to account for this, we additionally adjusted for a self-reported, recalled cancer or stroke diagnosis between 1991 and 2009 and self-reporting in midlife ever receiving a diagnosis of high blood pressure and/or diabetes and/or currently having high cholesterol.

Finally, we evaluated potential selection bias first in descriptive analyses by examining how sample characteristics changed with increasing sample restrictions. Then, we created stabilized inverse probability of selection weights (IPW) that modeled the probability of being in the final analytic sample (N = 2643) among all participants in NLSY79 in 1990 with 3+ measures of income, including at baseline (N = 7257), and we repeated main analyses weighting by these IPWs (details in **Supplemental Methods**). Finally, we also re-estimated main models applying NLSY79 custom sampling weights (*i.e.,* participants' weight for being in *any* survey wave between 1990 and 2016). However, the necessity and meaning of results using these weights when working with restricted (*e.g.,* complete case) and/or longitudinal samples is unclear (National Longitudinal Surveys). These sampling weights were normalized by dividing participants' weights by the sample mean weight.

3. Results

3.1. Sample characteristics

On average, the sample was 27.3 years old at baseline and included 51.4% female participants, 27.7% non-Hispanic Black participants, and 43.8% with >12 years of education (Table 1). Average income volatility (*i.e.,* intraindividual SD of the percent change in household income across successive surveys) was 54.2% with an SD of 36.2%. Average AFQT score was 46 percentage points. At baseline, median net family income was 27,000 (in current dollars) and average household size was

Table 1
Baseline characteristics[a] overall and according to number of income drops between 1990 and 2010 in our analytic sample of the National Longitudinal Survey of Youth (1979) (N = 2643).

		Number of income drops >25% from 1990 to 2010			
	Total	No drops	1 drop	2 drops	3+ drops
	(N = 2643)	(N = 577)	(N = 931)	(N = 650)	(N = 485)
Income volatility[b]					
Mean (SD)	54.2 (36.2)	23.3 (13.1)	47.9 (30.2)	65.7 (32.2)	87.9 (35.7)
Earlier-life cognition (AFQT score in 1980)[c]					
Mean (SD)	46.0 (28.9)	52.8 (27.4)	48.6 (28.9)	43.6 (29.6)	36.2 (26.7)
Age (years)					
Mean (SD)	27.3 (1.36)	27.5 (1.42)	27.3 (1.39)	27.2 (1.31)	27.2 (1.26)
Sex					
Male	1285 (48.6%)	289 (50.1%)	457 (49.1%)	312 (48.0%)	227 (46.8%)
Female	1358 (51.4%)	288 (49.9%)	474 (50.9%)	338 (52.0%)	258 (53.2%)
Race/ethnicity					
Black	731 (27.7%)	136 (23.6%)	254 (27.3%)	175 (26.9%)	166 (34.2%)
Hispanic	469 (17.7%)	94 (16.3%)	162 (17.4%)	120 (18.5%)	93 (19.2%)
Non-Hispanic, non-Black	1443 (54.6%)	347 (60.1%)	515 (55.3%)	355 (54.6%)	226 (46.6%)
Years of education					
≤ 12 years	1486 (56.2%)	274 (47.5%)	513 (55.1%)	366 (56.3%)	333 (68.7%)
>12 years	1157 (43.8%)	303 (52.5%)	418 (44.9%)	284 (43.7%)	152 (31.3%)
Marital status					
Married	1380 (52.2%)	361 (62.6%)	497 (53.4%)	316 (48.6%)	206 (42.5%)
Separated/ divorced/ widowed	322 (12.2%)	46 (8.0%)	106 (11.4%)	91 (14.0%)	79 (16.3%)
Never married	941 (35.6%)	170 (29.5%)	328 (35.2%)	243 (37.4%)	200 (41.2%)
Household size					
Mean (SD)	2.80 (1.50)	2.76 (1.41)	2.82 (1.50)	2.78 (1.53)	2.84 (1.57)
Body mass index					
Mean (SD)	25.4 (4.90)	25.7 (5.25)	25.3 (4.69)	25.1 (4.60)	25.8 (5.25)
Smoking status (1992)					
Current	833 (31.5%)	162 (28.1%)	252 (27.1%)	217 (33.4%)	202 (41.6%)
Former	302 (11.4%)	69 (12.0%)	113 (12.1%)	73 (11.2%)	47 (9.7%)
Never	1508 (57.1%)	346 (60.0%)	566 (60.8%)	360 (55.4%)	236 (48.7%)
CESD-20 score (1992)[d]					
CESD-20 score ≥ 16	511 (19.3%)	69 (12.0%)	159 (17.1%)	146 (22.5%)	137 (28.2%)
CESD-20 score <16	2132 (80.7%)	508 (88.0%)	772 (82.9%)	504 (77.5%)	348 (71.8%)
Health insurance type					
Employer provided	1438 (54.4%)	391 (67.8%)	543 (58.3%)	317 (48.8%)	187 (38.6%)
Other	737 (27.9%)	139 (24.1%)	239 (25.7%)	194 (29.8%)	165 (34.0%)
None	468 (17.7%)	47 (8.1%)	149 (16.0%)	139 (21.4%)	133 (27.4%)
Drinking status in past 30 days (1992)					
Heavy	261 (9.9%)	41 (7.1%)	84 (9.0%)	59 (9.1%)	77 (15.9%)
Light/ moderate	1417 (53.6%)	333 (57.7%)	485 (52.1%)	353 (54.3%)	246 (50.7%)
None	965 (36.5%)	203 (35.2%)	362 (38.9%)	238 (36.6%)	162 (33.4%)
Net family income (in 1990 dollars)[e]					
Mean (SD)	31,549 (24,680)	30,960 (16,118)	30,711 (22,307)	32,243 (26,947)	32,926 (32,886)
Median [Q1, Q3]	27,000 [15,000, 41,005]	29,949 [18,439, 40,212]	26,500 [16,000, 40,225]	27,000 [13,805, 43,000]	22,000 [10,488, 42,000]
Employment status[f]					
Works full-time	1918 (72.6%)	460 (79.7%)	704 (75.6%)	459 (70.6%)	295 (60.8%)
Works part-time	147 (5.6%)	27 (4.7%)	46 (4.9%)	38 (5.8%)	36 (7.4%)
Unemployed	439 (16.6%)	65 (11.3%)	139 (14.9%)	116 (17.8%)	119 (24.5%)
Disabled	62 (2.3%)	8 (1.4%)	13 (1.4%)	16 (2.5%)	25 (5.2%)
Not in labor force	77 (2.9%)	17 (2.9%)	29 (3.1%)	21 (3.2%)	10 (2.1%)
Net family wealth (in 1990 dollars)[e]					
Mean (SD)	37,490 (115,183)	36,082 (98,282)	31,033 (84,864)	38,521 (115,243)	50,257 (171,018)
Median [Q1, Q3]	10,035 [2,378, 33,000]	14,650 [4,200, 39,000]	9373 [2,525, 30,300]	9500 [2,000, 30,008]	6402 [1,200, 34,625]
Missing	*561 (21.2%)*	*117 (20.3%)*	*205 (22.0%)*	*130 (20.0%)*	*109 (22.5%)*

[a] Baseline characteristics are measured in 1990 unless otherwise specified.
[b] Income volatility = SD of percent change in income across successive surveys from 1990 to 2010.
[c] Percentile score (ranging from 0 to 100).
[d] Center for Epidemiological Studies-Depression.
[e] For descriptive purposes, 1990 total household income and net family wealth are reported in current dollars and are not equivalized for household size (which is also reported in Table 1).
[f] For descriptive purposes, we display a non-collapsed version of employment status in Table 1.

2.80. For comparison, Grasset's CARDIA sample was slightly older (mean age = 30.1) and had a higher proportion of female (56.4%), Black (45.7%), and more than high school educated participants (74.0%). Average 1990 income in Grasset's sample was $36,406 (vs. $31,549 in our sample), average household size was 2.93, and the SD of income volatility was similar at 34.5%. For reference, the federal median income in 1990 across all households was 29,943 (in current dollars) and average household size was 2.63 (United States Census Bureau, 2023).

The number of income drops over the exposure period ranged from 0 to 6 and 18% of the sample experienced 3 or more drops (Table 1). Participants with more income drops were more likely to be Black or Hispanic, female, or unmarried, have CESD-20 scores ≥16, and currently smoke or drink heavily; they were less likely to have >12 years of education, employer-provided health insurance, or work full-time. Participants experiencing more income drops also had lower median net family income and wealth. These trends were also seen in Grasset.

3.2. Associations between income volatility and cognitive outcomes

Table 2 presents associations of income volatility (per 1 SD increase) and number of income drops with midlife cognition scores (raw and standardized scores for global cognition and memory and attention domains). In fully adjusted models (**Model 3,** Table 2), each SD increase in income volatility was associated with 0.081 SD lower midlife global cognition z-score (95% CI: −0.121, −0.041). These findings were consistent with those for memory and attention domains, with slightly stronger associations observed for memory than attention. Higher income volatility was also associated with higher odds of cognitive impairment (OR = 1.18, 95% CI: 1.02, 1.36, Supplemental Table S2).

Table 2
Multivariable adjusted associations of income volatility and number of income drops (1990–2010) with raw and standardized global and domain-specific midlife cognitive scores[a] in a sample of the National Longitudinal Survey of Youth (1979) cohort (N = 2643).

	Model 1[d]	Model 2[e]	Model 3[f]
	β (95% CI)	**β (95% CI)**	**β (95% CI)**
Cognition raw scores (min-max)			
Memory domain score (2–20)			
Income volatility (per 1 SD)[b]	−0.283 (−0.421, −0.145)	−0.272 (−0.416, −0.128)	−0.273 (−0.418, −0.127)
No. of income drops[c]			
0 drops	Ref	Ref	Ref
1 drop	−0.083 (−0.427, 0.260)	−0.083 (−0.427, 0.262)	−0.107 (−0.452, 0.237)
2 drops	−0.222 (−0.595, 0.152)	−0.211 (−0.589, 0.166)	−0.277 (−0.657, 0.102)
3+ drops	−0.534 (−0.944, −0.123)	−0.471 (−0.888, −0.053)	−0.576 (−1.00, −0.151)
Attention domain score (0–7)			
Income volatility (per 1 SD)[b]	−0.089 (−0.146, −0.032)	−0.078 (−0.137, −0.018)	−0.071 (−0.131, −0.011)
No. of income drops[c]			
0 drops	Ref	Ref	Ref
1 drop	0.052 (−0.090, 0.194)	0.062 (−0.081, 0.205)	0.058 (−0.084, 0.201)
2 drops	−0.151 (−0.306, 0.003)	−0.131 (−0.287, 0.025)	−0.140 (−0.297, 0.017)
3+ drops	−0.136 (−0.306, 0.034)	−0.106 (−0.279, 0.066)	−0.117 (−0.293, 0.058)
TICS-m overall score (4–27)			
Income volatility (per 1 SD)[b]	−0.372 (−0.528, −0.216)	−0.349 (−0.512, −0.187)	−0.344 (−0.508, −0.180)
No. of income drops[c]			
0 drops	Ref	Ref	Ref
1 drop	−0.031 (−0.419, 0.356)	−0.021 (−0.410, 0.369)	−0.049 (−0.438, 0.340)
2 drops	−0.373 (−0.795, 0.049)	−0.343 (−0.769, 0.084)	−0.418 (−0.846, 0.011)
3+ drops	−0.669 (−1.133, −0.206)	−0.577 (−1.049, −0.105)	−0.693 (−1.172, −0.214)
Cognition z-scores (min-max)			
Memory domain score (-2.66-2.46)			
Income volatility (per 1 SD)[b]	−0.080 (−0.120, −0.041)	−0.077 (−0.118, −0.036)	−0.078 (−0.119, −0.036)
No. of income drops[c]			
0 drops	Ref	Ref	Ref
1 drop	−0.024 (−0.121, 0.074)	−0.023 (−0.121, 0.074)	−0.031 (−0.128, 0.067)
2 drops	−0.063 (−0.169, 0.043)	−0.060 (−0.167, 0.047)	−0.079 (−0.187, 0.029)
3+ drops	−0.152 (−0.268, −0.035)	−0.134 (−0.253, −0.015)	−0.164 (−0.284, −0.043)
Attention domain score (-5.63-0.70)			
Income volatility (per 1 SD)[b]	−0.063 (−0.103, −0.023)	−0.054 (−0.095, −0.012)	−0.048 (−0.090, −0.006)
No. of income drops[3]			
0 drops	Ref	Ref	Ref
1 drop	0.017 (−0.081, 0.116)	0.021 (−0.078, 0.120)	0.020 (−0.079, 0.119)
2 drops	−0.098 (−0.205, 0.010)	−0.085 (−0.193, 0.024)	−0.087 (−0.196, 0.022)
3+ drops	−0.118 (−0.236, 0.000)	−0.097 (−0.217, 0.023)	−0.097 (−0.220, 0.025)
TICS-m overall score (-5.00–2.04)			
Income volatility (per 1 SD)[b]	−0.093 (−0.131, −0.055)	−0.085 (−0.124, −0.045)	−0.081 (−0.121, −0.041)
No. of income drops[c]			
0 drops	Ref	Ref	Ref
1 drop	−0.004 (−0.099, 0.090)	−0.002 (−0.096, 0.093)	−0.007 (−0.102, 0.088)
2 drops	−0.104 (−0.207, −0.001)	−0.094 (−0.198, 0.010)	−0.107 (−0.212, −0.003)
3+ drops	−0.175 (−0.288, −0.062)	−0.150 (−0.264, −0.035)	−0.169 (−0.286, −0.052)

Ref = reference group; SD = standard deviation; No. = number.

[a] Cognition was captured from 2010 to 2016 in our sample using the modified Telephone Interview for Cognitive Status (TICS-m). Global cognition is assessed via the TICS-m overall score, which combines immediate and delayed 10-word recall tasks, backward counting tasks, and serial 7 subtraction. Memory subdomain scores were created by combining results for immediate and delayed recall tasks and attention scores were from combining backward counting and serial 7s scores.

[b] 1 SD increase in income volatility = 36.2 SD of percent change in income from 1990 to 2010; income from 1990 to 2010 was inflation-adjusted to 1990 dollars and equivalized for household size for income volatility calculations.

[c] Number of income drops >25% from 1990 to 2010; nominal income equivalized for household size was used to compute number of income drops from 1990 to 2010 to avoid capturing drops due to inflation alone.

[d] Model 1 adjusted for the number of income measures participants contributed to the exposure period, the year in which participants completed their 48+ cognitive module, earlier-life cognition (AFQT percentile score in 1980), and participants' baseline age, sex, racial/ethnic group membership, years of education, and marital status.

[e] Model 2 adjusted for all Model 1 covariates plus: participants' BMI in 1990, smoking status in 1992, depressive symptoms in 1992, health insurance status in 1990, and drinking status in 1992.

[f] Model 3 adjusted for all Model 2 covariates plus: participants' 1990 income (equivalized for household size) and employment status.

Experiencing 3+ income drops of >25% over the exposure period (vs. none) was associated with lower global cognition ($\widehat{\beta}$ = -0.169, 95% CI: −0.286, −0.052) and memory domain z-scores ($\widehat{\beta}$ = -0.164, 95% CI: −0.284, −0.043) in fully adjusted models (**Model 3,** Table 2). Associations between 3+ drops and attention z-scores were smaller in magnitude and not statistically significant ($\widehat{\beta}$ = -0.097, 95% CI: −0.220, 0.025). Participants experiencing 3+ income drops from 1990 to 2010 had 1.92 times the odds of cognitive impairment (95% CI: 1.18, 3.17) compared with those experiencing none (Supplemental Table S2).

3.3. Effect modification findings

Fully adjusted associations between income volatility and global cognition z-scores within strata of socioeconomic modifiers are shown in Fig. 2 (corresponding coefficients for all models are in Supplemental Table S3). Stronger negative associations were consistently observed in strata indicating fewer socioeconomic resource or more financial hardship (*e.g.,* for poverty status: $\widehat{\beta}_{\text{ever}} = -0.089$, 95% CI: −0.157, −0.021 vs. $\widehat{\beta}_{\text{never}} = 0.025$, 95% CI: −0.055, 0.105). Significant interactions were observed between income volatility and poverty status ($p_{int} = 0.015$), homeownership status ($p_{int} = 0.030$), educational attainment ($p_{int} = 0.00010$), and income class created using average 1990 income from 1990 to 2010 ($p_{int} = 0.0069$).

Supplemental Table S4 displays associations between income volatility and global cognition z-scores within strata of race and ethnicity, gender, and race, ethnicity, and gender considered simultaneously. Overall, associations were strongest for Black participants ($\widehat{\beta}$ = -0.103, 95% CI: −0.183, −0.022 vs. $\widehat{\beta}_{\text{Hispanic}} = -0.074$, 95% CI: −0.174, 0.025 and $\widehat{\beta}_{\text{non-Black/non-Hispanic}} = -0.044$, 95% CI: −0.097, 0.009) and slightly stronger for female ($\widehat{\beta}$ = -0.093, 95% CI: −0.150, −0.035) vs. male participants ($\widehat{\beta}$ = -0.065, 95% CI: −0.121, −0.008). In joint strata, these associations were strongest among Black male and Hispanic male participants.

3.4. Sensitivity analyses

Supplemental Table S5a-b shows that income volatility and experiencing 3+ income drops were negatively associated with z-scores (Table S5a) and raw scores (Table S5b) for all individual cognitive assessments, but with weaker evidence for backward counting and serial 7's. As expected, the SD of income volatility was smaller (30.0) when income values were carried forward between time points with missing

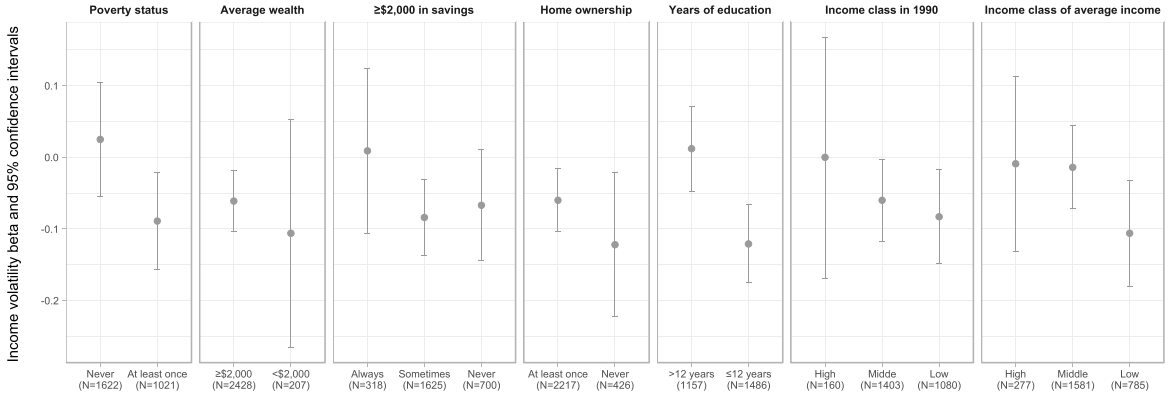


Fig. 2. Multivariable adjusted associations between income volatility (1990–2010) and midlife global cognition z-scores within strata of socioeconomic modifiers in a subsample of the National Longitudinal Survey of Youth (1979) cohort (N = 2643)

Fig. 2 footnote: Each plot displays the fully-adjusted linear regression coefficients and 95% confidence intervals for the relationship between a 1 SD increase in income volatility (SD of percent change in income across successive surveys from 1990 to 2010) and global cognition z-score (TICS-m) within strata of socioeconomic modifiers. Modifiers included (from left to rightmost plot): being in poverty at least once over the exposure period (vs. never), average family wealth over the exposure period (in 1990 dollars) valuing <$2000 (vs. ≥$2000), never reporting having $2000 or more in assets like a savings account over the exposure period (vs. sometimes vs. always), never reporting owning or making payments on a home over the exposure period (vs. at least once), having ≤12 years of education (vs. >12 years), being categorized as "low" income class in 1990 (vs. middle vs. high), and being categorized as "low" income class for average total household income (in 1990 dollars) over the exposure period (vs. middle vs. high). For income class, household income was equivalized to a household of 2 for comparison with the federal median income in 1990 for a household of two. Coefficients for all models are in Supplemental Table S3.

data; however, results were consistent using this alternative imputation approach (Supplemental Table S6). Findings were similar, albeit slightly attenuated (especially for number of income drops), when summaries of time-varying covariates were adjusted for instead of baseline values (Supplemental Table S7). Similar to main analyses, higher volatility associated with worse midlife cognitive function in analyses using alternative income volatility exposures (Supplemental Table S8). Findings were robust to additional adjustment for health shocks and chronic conditions (Supplemental Table S9).

Sample characteristics shifted only slightly from the initial sample of eligible participants in 1990 (N = 8953) and those who had ≥3 income measures including at baseline (N = 7257) to the analytic sample (N = 2643). However, the analytic sample had lower income volatility and higher AFQT percentile scores and educational attainment (Supplemental Table S10). This suggests exclusion from our sample depended on both exposure and outcome, since AFQT scores and educational attainment predict later cognition. Because individuals with higher income volatility and lower AFQT scores and educational attainment were disproportionately excluded from our sample, our findings are likely attenuated compared with what we would have observed if we had complete data for all eligible participants in 1990. Consistent with this, in sensitivity analyses using IPW, coefficients were slightly larger in magnitude when weighting to the sample of 7257 (Supplemental Table S11). Finally, applying custom NLSY79 sampling weights attenuated some coefficients but did not alter overall conclusions (Supplemental Table S12).

4. Discussion

In line with overall conclusions from Grasset et al., (2019), our study found that income volatility and number of income drops from early through middle adulthood were negatively associated with midlife cognitive function. We similarly observed that these findings were independent of adjustment for other socioeconomic risk factors–including income level–and held up in numerous sensitivity analyses. To help put our income volatility findings in context, the association we observed with global cognitive performance is consistent with the range of cognitive performance coinciding with one less year of education (~0.04–0.08 SD reduction) (Lövdén et al., 2020). Importantly, our findings were also independent of a measure of earlier-life cognitive skills. In fully adjusted models for global cognition z-scores, excluding adjustment for AFQT percentile score resulted in an income volatility coefficient of −0.095 (vs. −0.081, a 15% attenuation with AFQT adjustment) and a coefficient for 3+ drops of −0.253 (vs. −0.169, a 33% attenuation), but the direction and significance was unchanged. Thus, unmeasured confounding by earlier-life cognition is unlikely to be a plausible alternative explanation for our findings or Grasset's.

Although our general conclusions align with Grasset's, one key difference in our studies is that cognitive function is captured via different assessments in NLSY79 and CARDIA. Still, both studies captured aspects of memory (immediate/delayed recall vs. RAVLT) and attention (backward counting, serial 7's vs. DSST, Stroop), and Grasset's RAVLT results should be fairly comparable to our analyses using raw scores on immediate and delayed recall tasks, since these assessments capture similar constructs on similar scales. Indeed, focusing on analyses where our studies are most aligned (Model 1 analyses in our Supplemental Table S5b and Grasset's Table e3, where confounder adjustment was identical and where Grasset adjusts for earlier-life cognition by restricting analyses to participants with more than high school education) the magnitude of our findings is quite comparable. For example, income volatility results were $\widehat{\beta}$ = -0.124, 95% CI: −0.191, −0.057 for immediate recall and $\widehat{\beta}$ = -0.159, 95% CI: −0.243, −0.076 for delayed recall raw scores vs. $\widehat{\beta}$ = -0.09, 95% CI: −0.23, 0.05 for the RAVLT in Grasset. Similarly, results for the highest number of income drops were $\widehat{\beta}$ = -0.260, 95% CI: −0.459, −0.061 for immediate recall and $\widehat{\beta}$ = -0.273, 95% CI: −0.521, −0.025 for delayed recall raw scores vs. $\widehat{\beta}$ = -0.27, 95% CI: −0.69, 0.14 for the RAVLT in Grasset. Comparing results for attention assessments across studies is difficult given greater differences in raw scales of backward counting and serial 7's vs. DSST and Stroop.

Beyond replication, our study extended Grasset's analysis by exploring how associations between income volatility and cognition differed in the context of fewer financial resources and structural marginalization, to improve understanding of the contexts in which the harms of income volatility are exacerbated. Prior research suggests that the attention paid to stretching resources and absorbing income swings in the context of financial scarcity or limited resources can be

overwhelming, and this hyperfocus can consume mental capacities, depleting an individual's cognitive bandwidth (Appelhans, 2023; Gennetian and Shafir, 2015; Mani et al., 2013; Mullainathan and Shafir, 2013; Sayre, 2023). Our fully-adjusted stratum-specific findings lend support to this hypothesis, where income volatility was worse for cognitive function in every modifier strata that indicated fewer resources (*e.g.,* lower wealth and savings, lower education, never owning a home over the exposure period) or structural marginalization (*e.g.,* Black Americans – particularly Black men; those ever in poverty; those with low income). A deeper explanation for scarcity's effect on the brain may be that cumulative stress from chronic financial worries and mental preoccupation becomes embodied and causes dysregulation of multiple physiologic systems (*e.g.,* allostatic load) (Blair and Raver, 2016; Cunliffe, 2016; McEwen and Rasgon, 2018) which can accelerate biological aging and hasten the onset of age-related disease outcomes, including cognitive decline and dementia (McEwen and Rasgon, 2018; Schrempft et al., 2024). These findings should be corroborated, and thorough examination of these pathways should be conducted in future studies.

It is important to consider the economic landscape in which our findings can be interpreted. Income volatility has been increasing over time in the US (Addo and Servon, 2022; Duncan, 1996; Dynan et al., 2012; Gottschalk and Moffitt, 2009; Gottschalk et al., 1994; Hardy and Ziliak, 2014; Jacobs E & Hacker J, 2008), and prior research has documented that households experiencing income volatility (regardless of direction *i.e.,* gains or losses) report lower financial wellbeing than those with more stable incomes (The Pew Charitable Trusts, 2017). Further, the vast majority of Americans–including those living in poverty–report that financial stability matters more to them than moving up the income ladder (Morduch and Schneider, 2017; The Pew Charitable Trusts, 2015a). Thus, strengthening social safety net policies that improve household financial situations by relieving income volatility (*e.g.,* unemployment insurance, transfer payments) is likely of great public interest. In the context of our study, it is possible that enhancing policies that help smooth unpredictable income swings could alleviate financial stress (Batra A, Jackson K, & Hamad R, 2023; Carlson C & Marema T, 2024), offer stability and, in turn, reduce cognitive burden (Ong et al., 2019). Evaluating how the social policy context modifies the relationship between income volatility and cognitive health is a key next step for this research.

In addition to replicating Grasset's study design, controlling for earlier-life cognitive skills, and considering modifiers of income volatility, strengths of our study include more frequent follow-ups over our 20-year exposure period (13 time points vs. 6 in Grasset), which enabled us to compute yearly/biennial income volatility from 1990 to 2010. Our income measure is also a more robust measure with less measurement error than using the mid-point of a given income bracket to define income at each survey year, as had to be done using CARDIA data. Despite these differences, overall conclusions from both studies were quite similar.

Our study also has some limitations. While the thresholds defining our modifier strata (*e.g.,* $2000) were *a priori* specified based on the scarcity and financial fragility literature, we acknowledge that different thresholds (*e.g.,* sample-specific quantiles) could produce different results. Further, although their construction was theoretically motivated, some modifier categories were small, producing imprecise estimates; thus, our interpretation emphasizes the general pattern of associations for modifier analyses rather than statistical significance (*e.g.,* in line with expectations, across all examined modifiers we consistently observed stronger associations in the stratum indicating fewer resources). Despite using a national sample to address generalizability challenges in Grasset, our ability to draw inference to the US population is unclear after restricting to our longitudinal analytic sample (although conclusions held using various sample weighting approaches). Earlier-life cognitive skills in NLSY79 is captured using AFQT percentile scores, and although the AFQT has been purported to reflect general cognitive abilities (Cameron and Heckman, 1993; Holz and Tienda, 1998), others argue it may also or instead be capturing differences in material/structural resources (Cordero-Guzmán, 2001; Fischer et al., 2020). If AFQT is not entirely capturing cognitive function, some residual confounding by earlier-life cognition may remain, although it would be unlikely to explain our findings. We also lacked more specific measures of baseline health status available in Grasset, such as measured cholesterol and fasting glucose, although we attempted to deal with this by adjusting for strong predictors of these health markers, like health insurance and heavy drinking status. Additionally, robustly addressing time-varying confounding is complicated when time-varying exposures are summarized into exposure histories (Schwartz and Glymour, 2023). Adjusting for summaries of time-varying confounders (*e.g.,* average BMI from 1990 to 2010) may be inadequate or may introduce issues of overadjustment if a variable functions as both a confounder and mediator over time. In sensitivity analyses, we attempted to control for potential confounding events occurring over the exposure period by adjusting for confounder summaries, health shocks, and chronic conditions; however, residual confounding may remain. Further, we can only control for health events that are reported by participants, so unobserved health problems or health issues unreported by participants could likewise result in residual confounding.

Finally, perhaps the biggest challenge to fully replicating Grasset's findings is the difference in cognitive assessments between studies (Supplemental Table S1); we also lacked measures of brain markers in NLSY79, which Grasset examined in their study. However, an advantage of the TICS is that it is a widely used battery in longitudinal aging studies (De Looze et al., 2023), and it is highly correlated with other widely used batteries (like the Mini-Mental State Exam) (Fong et al., 2009), which helps enhance the generalizability of our findings. To further enhance comparability with other studies, we also presented results for raw and standardized global and domain-specific cognitive scores.

6. Conclusion

We found that income volatility assessed over 20-years from early-to-mid adulthood was negatively associated with midlife cognitive function, consistent with conclusions in Grasset et al., (2019). Findings were independent of earlier-life cognitive skills and baseline level of income. Our results add to a growing evidence base showing the cumulative harms of long-term financial instability on cognitive outcomes at older ages.

CRediT authorship contribution statement

Katrina L. Kezios: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Calvin L. Colvin:** Writing – review & editing, Validation, Resources, Formal analysis. **Leslie Grasset:** Writing – review & editing, Resources, Methodology, Investigation. **Catherine dP. Duarte:** Writing – review & editing, Methodology, Investigation. **M. Maria Glymour:** Writing – review & editing, Supervision, Methodology, Investigation. **Adina Zeki Al Hazzouri:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Ethical statement

This secondary analysis did not require IRB approval as it utilizes publicly available data, where participant identities are anonymized. We adhered to all ethical guidelines regarding data privacy and confidentiality, ensuring that the analysis does not allow for individual re-identification and that all findings are reported in a way that protects participant anonymity.

Funding

KLK was supported by National Institute on Aging (NIA) grant

K99AG084769; CLC was supported by NIA grant R01AG072681-03S1; CdPD was supported by the IDEAL Provostial Fellowship, Standford University; MMG and AZAH were supported by NIA grant R01AG072681.

Declaration of competing interest

None declared.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.117798.

Data availability

The dataset (NLSY79) is free and publicy available for download; we are happy to share analytic code on request.

References

Addo, M., Servon, L., 2022. Income Volatility and Healthcare Decision-Making. in.

American Psychological Association, 2023. Stress in America 2023 [Press release]. Retrieved from. https://www.apa.org/news/press/releases/stress/2023/collective-trauma-recovery.

Appelhans, B.M., 2023. The cognitive burden of poverty: a Mechanism of socioeconomic health disparities. American Journal of Preventive Medicine 64 (2), 293–297. https://doi.org/10.1016/j.amepre.2022.08.012.

Basu, S., 2017. Income volatility: a preventable public health threat. American Journal of Public Health 107 (12), 1898–1899. https://doi.org/10.2105/ajph.2017.304109.

Batra, A., Jackson, K., Hamad, R., 2023. Effects of the 2021 expanded child tax credit on adults' mental health: a quasi-experimental study. Health Affairs 42 (1), 74–82. https://doi.org/10.1377/hlthaff.2022.00733.

Bennett, R., 2023. Most Americans are significantly stressed about money - here's how it varies by demographics. Retrieved from. https://www.bankrate.com/banking/money-and-financial-stress-statistics/.

Biddinger, K.J., Emdin, C.A., Haas, M.E., Wang, M., Hindy, G., Ellinor, P.T., Aragam, K. G., 2022. Association of Habitual alcohol intake with risk of cardiovascular disease. JAMA Network Open 5 (3), e223849. https://doi.org/10.1001/jamanetworkopen.2022.3849.

Blair, C., Raver, C.C., 2016. Poverty, stress, and brain development: new directions for prevention and intervention. Acad Pediatr 16 (3 Suppl. l), S30–S36. https://doi.org/10.1016/j.acap.2016.01.010.

Brobeck, S., 2008. The Essential Role of Banks and Credit Unions in Facilitating Lower-Income Household Saving for Emergencies. Consumer Federation of America, Washington, DC.

Cameron, S.V., Heckman, J.J., 1993. The nonequivalence of high school equivalents. Journal of Labor Economics 11 (1), 1–47. https://doi.org/10.1086/298316. Part 1.

Carlew, A.R., Fatima, H., Livingstone, J.R., Reese, C., Lacritz, L., Pendergrass, C., Cullum, C.M., 2020. Cognitive assessment via telephone: a scoping review of instruments. Arch Clin Neuropsychol 35 (8), 1215–1233. https://doi.org/10.1093/arclin/acaa096.

Carlson, C., Marema, T., 2024. 2021 child-tax-credit expansion lowered family stress and improved mental health. Retrieved from. https://dailyyonder.com/child-tax-credit-expansion-lowered-family-stress-and-improved-mental-health/2024/02/02/.

Chen, R., Williams, D.R., Nishimi, K., Slopen, N., Kubzansky, L.D., Weuve, J., 2022. A life course approach to understanding stress exposures and cognitive function among middle-aged and older adults. Social Science & Medicine 314, 115448. https://doi.org/10.1016/j.socscimed.2022.115448.

Cheng, S., 2014. A life course trajectory framework for understanding the intracohort pattern of wage inequality. American Journal of Sociology 120 (3), 633–700. https://doi.org/10.1086/679103.

Cordero-Guzmán, H.R., 2001. Cognitive skills, test scores, and social stratification: the role of family and school-level resources on racial/ethnic differences in scores on standardized tests (Afqt). The Review of Black Political Economy 28 (4), 31–71. https://doi.org/10.1007/s12114-001-1008-2.

Cox, R.J.A., Wallace, R.B., 2022. The role of Incarceration as a risk factor for cognitive impairment. The Journals of Gerontology: Series B 77 (12), e247–e262. https://doi.org/10.1093/geronb/gbac138.

Cunliffe, V.T., 2016. The epigenetic impacts of social stress: how does social adversity become biologically embedded? Epigenomics 8 (12), 1653–1669.

Dahl, M., DeLeire, T., Schwabish, J.A., 2011. Estimates of year-to-year volatility in earnings and in household incomes from administrative, survey, and matched data. Journal of Human Resources 46 (4), 750–774. https://doi.org/10.3368/jhr.46.4.750.

De Looze, C., Feeney, J., Seeher, K.M., Amuthavalli Thiyagarajan, J., Diaz, T., Kenny, R. A., 2023. Assessing cognitive function in longitudinal studies of ageing worldwide: some practical considerations. Age and Ageing 52 (Suppl. ment_4), iv13–iv25. https://doi.org/10.1093/ageing/afad122.

Dickler, J., 2017. No. 1 cause of money stress: when expenses exceed income. Retrieved from. https://www.cnbc.com/2017/06/26/greatest-cause-of-money-stress-when-expenses-exceed-income.html.

Dickler, J., 2023. 62% of Americans are still living paycheck to paycheck, making it 'the main financial lifestyle,' report finds. Retrieved from. https://www.cnbc.com/2023/10/31/62percent-of-americans-still-live-paycheck-to-paycheck-amid-inflation.html.

Duncan, G.J., 1996. Income dynamics and health. International Journal of Health Services 26 (3), 419–444. https://doi.org/10.2190/1ku0-4y3k-acfl-byu7.

Dynan, K., Elmendorf, D., Sichel, D., 2012. The evolution of household income volatility. The B.E. Journal of Economic Analysis & Policy 12 (2). https://doi.org/10.1515/1935-1682.3347.

Elfassy, T., Swift, S.L., Glymour, M.M., Calonico, S., Jacobs Jr., D.R., Mayeda, E.R., Zeki Al Hazzouri, A., 2019. Associations of income volatility with incident cardiovascular disease and all-cause mortality in a US cohort. Circulation 139 (7), 850–859. https://doi.org/10.1161/circulationaha.118.035521.

Federal Reserve Bank of Minneapolis. Inflation Calculator. Retrieved from https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator.

Fischer, C.S., Hout, M., Jankowski, M.S., Lucas, S.R., Swidler, A., Voss, K., 2020. Inequality by Design: Cracking the Bell Curve Myth. Princeton University Press.

Fong, T.G., Fearing, M.A., Jones, R.N., Shi, P., Marcantonio, E.R., Rudolph, J.L., Inouye, S.K., 2009. Telephone interview for cognitive status: creating a crosswalk with the mini-mental state examination. Alzheimers Dement 5 (6), 492–497. https://doi.org/10.1016/j.jalz.2009.02.007.

Gennetian, L.A., Hardy, B., 2023. The financial and psychological costs of income volatility. Retrieved from. https://econofact.org/the-financial-and-psychological-costs-of-income-volatility.

Gennetian, L.A., Shafir, E., 2015. The persistence of poverty in the context of financial instability: a behavioral perspective. Journal of Policy Analysis and Management 34 (4), 904–936. https://doi.org/10.1002/pam.21854.

Gottschalk, P., Moffitt, R., 2009. The rising instability of US earnings. Journal of Economic Perspectives 23 (4), 3–24.

Gottschalk, P., Moffitt, R., Katz, L.F., Dickens, W.T., 1994. The growth of earnings instability in the US labor market. Brookings Papers on Economic Activity 1994 (2), 217–272.

Grasset, L., Glymour, M.M., Elfassy, T., Swift, S.L., Yaffe, K., Singh-Manoux, A., Zeki Al Hazzouri, A., 2019. Relation between 20-year income volatility and brain health in midlife: the CARDIA study. Neurology 93 (20), e1890–e1899. https://doi.org/10.1212/wnl.0000000000008463.

Grinstein-Weiss, M., Russell, B., Tucker, B., Comer, K., 2014. Lack of Emergency Savings Puts American Households at Risk: Evidence from the Refund to Savings Initiative. Policy Brief, p. 14, 13.

Gu, Q., Burt, V.L., Dillon, C.F., Yoon, S., 2012. Trends in antihypertensive medication use and blood pressure control among United States adults with hypertension. Circulation 126 (17), 2105–2114. https://doi.org/10.1161/CIRCULATIONAHA.112.096156.

Hardy, B., Ziliak, J.P., 2014. Decomposing trends in income volatility: the "wild ride" at the top and bottom. Economic Inquiry 52 (1), 459–476. https://doi.org/10.1111/ecin.12044.

Holz, V., Tienda, M., 1998. Education and employment in a diverse society: generating inequality through the school to work transition. American diversity: A demographic challenge for the twenty-first century 249–281.

Homan, P., 2019. Structural sexism and health in the United States: a new perspective on health inequality and the gender system. American Sociological Review 84 (3), 486–516. https://doi.org/10.1177/0003122419848723.

Jacobs, E., Hacker, J., 2008. The rising instability of American family incomes, 1969-2004: evidence from the panel study of income dynamics. Retrieved from. https://www.epi.org/publication/bp213/.

Kulshreshtha, A., Alonso, A., McClure, L.A., Hajjar, I., Manly, J.J., Judd, S., 2023. Association of stress with cognitive function among older Black and white US adults. JAMA Netw Open 6 (3), e231860. https://doi.org/10.1001/jamanetworkopen.2023.1860.

Lett, E., Asabor, E., Beltrán, S., Cannon, A.M., Arah, O.A., 2022. Conceptualizing, contextualizing, and operationalizing race in quantitative health sciences research. Ann Fam Med 20 (2), 157–163. https://doi.org/10.1370/afm.2792.

Liu, A., Cheng, S., 2023. Family structure and cohort trends in childhood family income volatility. Socius 9, 23780231231182515. https://doi.org/10.1177/23780231231182515.

Lövdén, M., Fratiglioni, L., Glymour, M.M., Lindenberger, U., Tucker-Drob, E.M., 2020. Education and cognitive functioning across the life span. Psychological Science in the Public Interest 21 (1), 6–41. https://doi.org/10.1177/1529100620920576.

Lusardi, A., Schneider, D.J., Tufano, P., 2011. Financially fragile households: evidence and implications. Retrieved from. https://www.nber.org/papers/w17072.

Lynch, J.W., Kaplan, G.A., Shema, S.J., 1997. Cumulative impact of sustained economic hardship on physical, cognitive, psychological, and social functioning. N Engl J Med 337 (26), 1889–1895. https://doi.org/10.1056/nejm199712253372606.

Lyu, J., Burr, J.A., 2016. Socioeconomic status across the life course and cognitive function among older adults:an examination of the latency, pathways, and accumulation hypotheses. Journal of Aging and Health 28 (1), 40–67. https://doi.org/10.1177/0898264315585504.

Mani, A., Mullainathan, S., Shafir, E., Zhao, J., 2013. Poverty impedes cognitive function. Science 341 (6149), 976–980. https://doi.org/10.1126/science.1238041.

Marden, J.R., Tchetgen Tchetgen, E.J., Kawachi, I., Glymour, M.M., 2017. Contribution of socioeconomic status at 3 life-course periods to late-life memory function and decline: early and late predictors of dementia risk. American journal of epidemiology 186 (7), 805–814.

Mason, K., 2012. The unequal weight of discrimination: gender, body size, and income inequality. Social Problems 59 (3), 411–435. https://doi.org/10.1525/sp.2012.59.3.411.
McEwen, B.S., Rasgon, N.L., 2018. The brain and body on stress: allostatic load and mechanisms for depression and dementia. In: Strain, J.J., Blumenfield, M. (Eds.), Depression as a Systemic Illness. Oxford University Press, pp. 14–36.
Morabito, C., 2023. Here's why even Americans making more than $100,000 live paycheck to paycheck. Retrieved from. https://www.cnbc.com/2023/12/11/why-even-americans-making-more-than-100000-live-paycheck-to-paycheck.html.
Morduch, J., Schneider, R., 2017. The Financial Diaries: How American Families Cope in a World of Uncertainty. Princeton University Press.
Mullainathan, S., Shafir, E., 2013. Scarcity: Why Having Too Little Means So Much. Macmillan.
National Longitudinal Surveys. Sample Weights & Clustering Adjustments. Retrieved from https://www.nlsinfo.org/content/cohorts/nlsy79/using-and-understanding-the-data/sample-weights-clustering-adjustments.
Ong, Q., Theseira, W., Ng, I.Y.H., 2019. Reducing debt improves psychological functioning and changes decision-making in the poor. Proceedings of the National Academy of Sciences 116 (15), 7244–7249. https://doi.org/10.1073/pnas.1810901116.
Pew Research Center, 2016. America's shrinking middle class: a close look at changes within metropolitan areas. Retrieved from. https://www.pewresearch.org/social-trends/2016/05/11/americas-shrinking-middle-class-a-close-look-at-changes-within-metropolitan-areas/.
Prause, J., Dooley, D., Huh, J., 2009. Income volatility and psychological depression. Am J Community Psychol 43 (1–2), 57–70. https://doi.org/10.1007/s10464-008-9219-3.
Reeves, R.V., Pulliam, C., 2019. Tipping the balance: why equivalence scales matter more than you think. Retrieved from. https://www.brookings.edu/articles/whats-in-an-equivalence-scale-maybe-more-than-you-think/.
Rosenberg, S.J., Ryan, J.J., Prifitera, A., 1984. Rey Auditory-Verbal Learning Test performance of patients with and without memory impairment. J Clin Psychol 40 (3), 785–787. https://doi.org/10.1002/1097-4679(198405)40:3<785::aid-jclp2270400325>3.0.co;2-4.
Rothstein, D.S., Carr, D., Cooksey, E., 2019. Cohort profile: the national longitudinal survey of Youth 1979 (NLSY79). Int J Epidemiol 48 (1), 22. https://doi.org/10.1093/ije/dyy133, 22e.
Runge, S.K., Craig, B.M., Jim, H.S., 2015. Word recall: cognitive performance within internet surveys. JMIR Ment Health 2 (2), e20. https://doi.org/10.2196/mental.3969.
Sayre, G.M., 2023. The costs of insecurity: pay volatility and health outcomes. Journal of Applied Psychology 108 (7), 1223–1243. https://doi.org/10.1037/apl0001062.
Schrempft, S., Trofimova, O., Künzi, M., Ramponi, C., Lutti, A., Kherif, F., Draganski, B., 2024. The neurobiology of life course socioeconomic conditions and associated cognitive performance in middle to late adulthood. The Journal of Neuroscience 44 (17), e1231232024. https://doi.org/10.1523/jneurosci.1231-23.2024.
Schwartz, G.L., Glymour, M.M., 2023. Bridging the divide: tackling tensions between life-course Epidemiology and causal inference. Annual Review of Developmental Psychology 5 (2023), 355–374. https://doi.org/10.1146/annurev-devpsych-120221-033623, 5.
Stroop, J.R., 1935. Studies of interference in serial verbal reactions. Journal of Experimental Psychology 18 (6), 643–662. https://doi.org/10.1037/h0054651.
The Expanding Prosperity Impact Collaborative, 2016. Income Volatility. A Primer. Retrieved from. https://www.aspeninstitute.org/publications/income-volatility-a-primer/.
The Pew Charitable Trusts, 2015a. Americans' financial security: perception and reality. Retrieved from. https://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2015/02/americans-financial-security-perceptions-and-reality.
The Pew Charitable Trusts, 2015b. The role of emergency savings in family financial security: how do families cope with financial shocks? Retrieved from. https://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2015/10/the-role-of-emergency-savings-in-family-financial-security-how-do-families.
The Pew Charitable Trusts, 2017. How income volatility interacts with American families' financial security: an examination of gains, losses, and household economic experiences. Retrieved from. https://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2017/03/how-income-volatility-interacts-with-american-families-financial-security.
Turrell, G., Lynch, J.W., Kaplan, G.A., Everson, S.A., Helkala, E.-L., Kauhanen, J., Salonen, J.T., 2002. Socioeconomic position across the lifecourse and cognitive function in late middle age. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 57 (1), S43–S51.
United States Census Bureau, 2023. Historical income tables: households. Retrieved from. https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-income-households.html.
Wang, A.-Y., Hu, H.-Y., Ou, Y.-N., Wang, Z.-T., Ma, Y.-H., Tan, L., Yu, J.-T., 2023. Socioeconomic status and risks of cognitive impairment and dementia: a systematic review and meta-analysis of 39 prospective studies. The journal of prevention of Alzheimer's disease 10 (1), 83–94.
Wechsler, D., 1997. Wechsler Adult Intelligence Scale-III *(No Title)*.
Wilper, A.P., Woolhandler, S., Lasser, K.E., McCormick, D., Bor, D.H., Himmelstein, D.U., 2009. Health insurance and mortality in US adults. American Journal of Public Health 99 (12), 2289–2295.
Wolfe, J.D., 2022. The financial correlates of midlife obesity. American Journal of Preventive Medicine 63 (1), S18–S27. https://doi.org/10.1016/j.amepre.2022.02.013. Supplement 1.
Zeki Al Hazzouri, A., Elfassy, T., Sidney, S., Jacobs, D., Pérez Stable, E.J., Yaffe, K., 2017. Sustained economic hardship and cognitive function: the coronary Artery risk development in Young adults study. Am J Prev Med 52 (1), 1–9. https://doi.org/10.1016/j.amepre.2016.08.009.
Ziliak, J.P., Hardy, B., Bollinger, C., 2011. Earnings volatility in America: evidence from matched CPS. Labour Economics 18 (6), 742–754.