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Durable Disruption and Compounding Disparities: Pre-pandemic Health Vulnerabilities and COVID-Related Elevation in Depression Trajectories Among U.S. Older Adults

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Abstract

Purpose: This study examines two questions: (1) How did depressive symptoms among U.S. older adults change during the outbreak (2020) and extended COVID pandemic period (2022)? and (2) How did pre-existing health vulnerabilities (*chronic conditions, functional limitations, self-rated poor health, emotional/psychiatric problems*) predict these changes?

Methods: We used data from the Health and Retirement Study (2010–2022). Analytic sample (N = 8,284) included respondents with depressive symptoms data in 2010-2022 to model pre- and post-pandemic trajectory change. Latent change score models estimated biennial changes of depressive symptoms, with pre-pandemic health vulnerabilities predicting changes in 2018–2020 and 2020–2022.

Results: Depressive symptoms remained stable (2010–2018), rose sharply (2018–2020), then plateaued through 2022. Disparities widened at outbreak: poorer self-rated health, greater functional limitations, and psychiatric history predicted disproportionately larger symptom increases. From 2020–2022, disparities tied to functional limitations and psychiatric history stabilized, while poor/fair self-rated health disparities continued to deepen.

Conclusion: COVID-19 established a higher post-pandemic baseline of depressive symptoms and compounded disadvantage among health-vulnerable older adults. Mental health services for this group should not assume a natural post-pandemic recovery but instead be prepared to address persistently elevated levels of depression in the post-pandemic period. Future research should extend tracking beyond 2022 and identify potential resilience factors.

Keywords: Chronic conditions; Depressive symptoms; Functional limitations; Latent change score model; Self-rated Health

1. Introduction

Over the past five years, the global COVID-19 pandemic has reshaped daily life in ways few could have anticipated. For the aging U.S. population, which is already carrying a disproportionate burden of chronic illness and health disparities, the pandemic brought layered challenges, from heightened risks of morbidity and mortality to disruptions in social support and health care access [1, 2]. Beyond its immediate public health consequences, COVID-19 continues to reverberate across social institutions, raising enduring concerns about the mental health of the aging population.

Earlier research found an abrupt rise in depressive symptoms among older adults in the U.S. and Europe during the COVID-19 outbreak, but data limitations have left unclear whether this spike reflected a short-term shock or a more lasting disruption [3, 4]. While recent evidence from Germany and Switzerland suggests no widespread chronic elevation in depressive symptoms two years after the outbreak in the general population [5], comparable longitudinal assessments focusing specifically on older adults in the United States remain scarce.

This gap is especially consequential because older adults with pre-existing health problems faced elevated risks of depression even before the pandemic [6]. Chronic conditions and functional limitations are highly prevalent in later life: more than three-quarters of U.S. adults aged 65 and older live with at least one chronic condition, and nearly half report difficulty with mobility or daily functioning [7]. These physical health challenges are closely intertwined with mental health, as they limit social participation, increase dependence on others, and contribute to feelings of isolation and psychological distress [8, 9]. Older adults with existing health challenges were already at elevated risk of poor mental health before the COVID-19 pandemic [6, 10]. If these groups experienced steeper increases in depressive symptoms during the pandemic, it would suggest that COVID-19 not only elevated distress broadly but also amplified existing inequalities — a finding with important implications for resource allocation and crisis preparedness.

Against this backdrop, this study addresses two related questions: *1) Did COVID-19 trigger an acute or persistent disruption in the depressive symptoms trajectories among older adults*? and 2*) Did pre-pandemic health vulnerabilities compound the mental health impact of COVID-19?* Addressing these questions is critical for determining whether mental health among older adults is likely to bounce back or remain durably altered following large-scale crises. Clarifying how pre-existing health vulnerabilities shape these trajectories is essential for identifying groups at greatest risk and for informing more equitable mental health and public health responses in future emergencies.

2. Hypotheses

Research on disasters shows that extreme events can trigger both acute and long-lasting mental health disruptions[11–13]. The COVID-19 pandemic, given its global reach, prolonged duration, and disruption of multiple domains of daily life, constitutes an especially profound macro-level stressor. Studies from Europe and the U.S. reported significant increases in depressive symptoms among older adults during the outbreak [14–17]. Yet it remains unclear whether these changes reflected a short-term spike or a lasting shift.

Prior disaster research suggests that while some populations demonstrate resilience, others—particularly those already vulnerable—experience enduring psychological scarring [18]. COVID-19's prolonged uncertainty, recurrent infection waves, and ongoing disruptions to healthcare, employment, and social life suggest that recovery for older adults may be slow, if it occurs at all. Recent evidence from Germany and Switzerland indicates that most of the general population did not experience chronically elevated depressive symptoms following the COVID-19 outbreak, pointing to substantial population-level resilience (Prati & Mancini, 2024). However, this work did not identify which groups were most vulnerable to persistent distress. Older adults are plausibly among those at elevated risk, yet data limitations have left this question largely unexamined. The availability of the 2022 Health and Retirement

Study data provides a unique opportunity to assess these dynamics. Rather than expecting a rapid rebound, we hypothesize that:

Hypothesis 1 (H1): Depressive symptoms among older adults rose sharply during the 2020 outbreak and remained elevated through 2022, indicating a durable rather than transient disruption.

Even before COVID-19, chronic illness, poor self-rated health, and functional limitations were well-established predictors of elevated depressive symptoms among older adults [9, 10, 19]. These vulnerabilities restricted mobility and daily functioning, heightened pain, and increased exposure to social and economic insecurity [6]. The pandemic magnified these challenges, as those with health problems faced greater barriers to healthcare and community services, along with elevated infection risks [20–22].

According to the *cumulative inequality theory*, crises such as COVID-19 may operate as an "inequality amplifier" by layering new stressors on top of existing disadvantages and therefore widening social gaps [23]. The extended observation window through 2022 allows assessment of whether health disparities reflected an acute reaction or a persistent widening. If older adults with poor pre-pandemic health experienced sharper increases in depressive symptoms in 2020, this would indicate that the outbreak immediately intensified inequality.

Hypothesis 2 (H2): Older adults with poorer pre-pandemic health experienced greater increases in depressive symptoms during the outbreak stage (2020).

Whether these disparities persisted is also crucial. If vulnerable groups remained at higher symptom levels through 2022 while healthier peers recovered, this would signal durable inequality amplification. COVID-19's repeated waves, prolonged healthcare disruptions, and social restrictions [24, 25] likely prolonged stressors for those already facing chronic illness or limited mobility. Continued barriers to medical care, support services, and community resources, combined with elevated infection and mortality risks, make rapid mental health recovery unlikely.

Hypothesis 3 (H3): Health-related disparities in depressive symptoms persisted through 2022, with older adults facing pre-existing vulnerabilities remaining at higher symptom plateaus.

2. Methods

2.1 Data

This study used data from the *Health and Retirement Study* (HRS), a nationally representative longitudinal survey of U.S. adults aged 50 and older conducted biennially since 1992 [26]. The HRS collects extensive information on health, socioeconomic status, family networks, and psychosocial well-being, making it well-suited for studying aging and mental health. We analyzed data spanning 2010–2022, a time window that covers multiple pre-pandemic waves, the initial outbreak (2018–2020), and the extended pandemic period (2020–2022).

To construct the analytic sample, we started with all HRS respondents who had a non-zero survey weight in 2010 (N = 20,337). Starting in 2010 offered two advantages: first, it provided a sufficiently long pre-pandemic window to model depressive symptom trajectories to facilitate differentiate normative and disruptive trends; second, it captured the entry of the mid–baby boomer cohort (born 1954–1959) and therefore maximized the sample size. From there, we included all respondents with complete data across the 2010–2022 period to allow robust modeling of pre- and post-pandemic depressive symptom trajectories. More than half of the 2010 respondents were excluded due to non-response in 2020 and 2022 (N=11,990), since without such information we could not determine the pre- and post-outbreak change. We further excluded 30 respondents with fewer than three waves of data between 2010 and 2018 to ensure reliable estimation of pre-pandemic trajectories, along with 33 respondents with missing data on depressive symptoms. The final Analytic Sample consisted of 8,284 respondents.

Because the analytic sample involved exclusions due to attrition, nonresponse, and missing data, we implemented a set of weight adjustments to correct for potential selection bias. The final analytic weights

combined the baseline 2010 survey weights with nonresponse adjustments and post-stratification to 2010 U.S. population benchmarks. These adjusted weights ensured that the analytic sample remained representative of older U.S. adults born before 1960. Technical details on the weights construction were provided in Appendix A.

2.2 Measures

Depressive symptoms.

Depressive symptoms were assessed as a latent variable in each wave based on the 8-item brief Center for Epidemiologic Studies Depression Scale (CESD-8) asking whether the respondent had following set of affective and somatic symptoms during the past week: *everything was an effort, sleep was restless, felt happy (reverse coded), felt lonely, enjoyed life (reverse coded), felt sad, had a lot of energy (reverse coded), and could not get going.* In each wave, these items were modeled as indicators of a latent depressive symptom construct using an item response theory (IRT) model.

Health vulnerabilities.

Pre-pandemic health vulnerability was captured using four indicators, all measured in the 2018 wave: self-rated health, chronic conditions, emotional/psychiatric problems, and functional limitation. First, respondents rated their overall health on a five-point scale ranging from *poor* to *excellent*, which we dichotomized into poor/fair (coded 1) versus good/very good/excellent (coded 0). Second, a count of chronic conditions was constructed based on whether respondents reported having any of 11 major conditions: hypertension, diabetes, heart disease, stroke, cancer, lung disease, arthritis, Alzheimer's disease or dementia, or obesity. Obesity was determined using the highest self-reported BMI between 2010 and 2018, while all other conditions were coded based on whether respondents had ever reported a physician's diagnosis. Third, a separate binary indicator captured whether a doctor had ever diagnosed the respondent with emotional or psychiatric problems, due to its distinct conceptual relationship with depressive symptoms. Finally, we measured functional limitation as the sum of 24 binary items covering

difficulties in activities of daily living (ADLs), instrumental activities of daily living (IADLs), and mobility tasks (For all items see Appendix B). Together, these measures provide a multidimensional assessment of health status immediately before the onset of the pandemic.

Covariates.

All models included a rich set of demographic, socioeconomic, and contextual covariates. Demographic factors included age, sex, race/ethnicity (White, Black, Hispanic, and other), and marital status (married/partnered, divorced/separated/widowed, or never married). Socioeconomic measures included years of education, average family income and wealth between 2016 and 2018 (log-transformed), and employment status in 2018. we also adjusted for birth cohort (Ahead/CODA, HRS, War Babies, Early Boomers, and Mid Boomers), residential location (urban, suburban, or rural), and religious attendance in 2018, measured on a scale from 1 (*not at all*) to 5 (*more than once a week*). To account for the timing of data collection during the pandemic, we included indicators for whether the 2020 interview was conducted between March–May, June–October, or November 2020–May 2021.

2.3 Analytic Strategy

To test H1 (i.e., population-level acute and persistent disruption), we estimated latent change score models (LCSM) across the 2010–2022 observation window. LCSM explicitly models change as a latent variable to purge measurement error from the true change score. This allows us to control problems like regression to the mean and low reliability (McArdle 2009; Hamaker, Kuiper, and Grasman 2015). Moreover, compared to more widely used latent growth curve models, which use smooth curves to represent trajectories, LCSM, as a more general framework, provides more flexibility to handle complex temporal trends by estimating discrete changes between two consecutive time points. This is critical for identifying disruptive trends. All analyses were performed using Mplus 8. Detailed model specifications were provided in Appendix C.

3. Results

3.1 Sample Characteristics

Table 1 summarizes the weighted characteristics of the analytic sample. The analytic sample was highly similar to 2010 U.S. population benchmarks across demographic, socioeconomic, and health domains due to post-stratification. In terms of pre-pandemic health profiles, there were on average 4.19 functional limitations and 2.71 chronic conditions reported, with 25% reporting poor or fair health. Demographically, about 46% were male; 78% were White, 10% Black, 9% Hispanic, and 3% other. Education averaged 13 years; 58% were married, 36% divorced, separated, or widowed, and 6% never married. Average income (2016–2018) was $82,500, and wealth averaged $660,000. Around 30% were employed, and roughly half lived in urban areas. Religious attendance averaged 2.7 on a 1–5 scale. Interview timing in 2020 was concentrated between June and October (60%).

[Table 1 about here]

3.2 Depressive Symptoms

Figure 1 shows endorsement trends for the eight CESD-8 items from 2010–2022. Six affective indicators—feeling sad, depressed, lonely, happy (reverse), enjoyed life (reverse), and trouble "getting going"—showed sharp increases between 2018 and 2020, breaking from previously stable trends. Although some declined slightly by 2022, levels remained elevated, indicating incomplete recovery. In contrast, two somatic items ("everything felt like an effort" and "restless sleep") changed little. This divergence between affective and somatic items suggests that different types of depressive symptoms responded differently to the pandemic. Simply adding or averaging all items, which assumes that all are equally good at distinguishing between low and high levels of depression, may therefore obscure the pandemic's impact on temporal trends.

[Fig. 1 about here]

Table 2 presents standardized factor loadings for the latent depressive symptom construct across waves. Loadings were consistently high, confirming strong measurement properties. Affective items ("felt depressed," "felt sad," "enjoyed life") loaded most strongly (>0.85), while "restless sleep" loaded weakest, suggesting that it cannot as strongly differentiate the population in terms of the latent trait of depressive symptoms. This pattern is understandable given that many older adults may experience restless sleep due to physical discomfort or pain rather than depressive mood [27]. Although the measurement model constrained factor loadings to be equal across waves, the standardized estimates showed slight variation over time due to small differences in cross-wave variances.

[Table 2 about here]

3.3 Population-Level Disruption in Depressive Symptoms (H1)

Figure 2 displays latent change scores in depressive symptoms. Between 2010 and 2018, changes were small and nonsignificant, indicating stable pre-pandemic trajectories. Between 2018 and 2020, however, depressive symptoms rose significantly (intercept = 0.16, SE = 0.05, $p < .001$), marking a sharp upward shift during the pandemic outbreak. From 2020 to 2022, the change was nonsignificant (intercept = –0.003, SE = 0.04, $p = .94$), showing that symptoms neither declined nor rose further but remained elevated. These results support H1: COVID-19 caused a structural disruption in depressive symptom trajectories, characterized by an abrupt increase and persistence at higher levels.

[Fig.2 about here]

3.4 Health Disparities and Inequality Amplification (H2 and H3)

Table 3 presents result in depression disparities based on pre-existing health vulnerabilities. Consistent with H2, older adults with poorer pre-pandemic health experienced greater increases in depressive symptoms during 2018–2020. Emotional or psychiatric problems ($\beta = 0.64$, $p < .001$), poor/fair self-rated

health ($\beta = 0.33$, $p < .001$), and functional limitations ($\beta = 0.07$, $p < .001$) all predict larger increases. Chronic physical conditions (excluding psychiatric) were nonsignificant ($\beta = –0.00$, n.s.). These coefficients are y-standardized; for instance, older adults with psychiatric problems saw a 0.64 SD larger increase in depressive symptoms compared to those without, beyond the overall population rise. Thus, while symptoms increased for all, health-vulnerable individuals experienced disproportionately greater deterioration, confirming inequality amplification during the outbreak.

For H3, assessing 2020–2022 change, most disparities stabilized. Functional limitations and psychiatric problems no longer predicted additional increases. However, poor/fair self-rated health remained a significant predictor ($\beta = 0.17$, $p = .013$), suggesting sustained vulnerability tied to subjective health perception rather than objective illness. These results partially support H3: disparities tied to functional and psychiatric limitations plateaued after 2020, but disparities based on self-rated health persisted and widened.

[Table 3 about here]

3.5 Covariates

Across models, several covariates showed consistent associations with changes in depressive symptoms. Men experienced smaller increases than women, and lower income predicted larger increases, reflecting economic vulnerability. Being unmarried (divorced, widowed, or never married) was linked to higher increases, while frequent in-person contact predicted smaller ones, even after controlling for digital communication. Suburban residence was modestly protective relative to urban living. These findings underscore that mental health deterioration during COVID-19 was concentrated among women, those with limited financial and social resources, and individuals lacking strong interpersonal support, whereas social connectedness provided resilience.

4. Conclusion

This study examined two questions: (1) Did COVID-19 trigger an acute or persistent disruption in depressive symptom trajectories among older adults? (2) Did pre-pandemic health vulnerabilities compound the mental health impact of COVID-19?

Findings reveal that depressive symptoms among older adults rose sharply between 2018 and 2020 and remained elevated through 2022, suggesting a persistent disruption rather than a temporary shock. This pattern indicates that COVID-19 fundamentally altered depressive symptom trajectories, consistent with prior research showing that large-scale disasters often leave lasting "scars" on population mental health [28, 29]. These findings contrast with evidence from Germany and Switzerland showing that only a small fraction of the general population experienced elevated depressive symptoms two years after the COVID-19 outbreak [5]. The divergence suggests that U.S. older adults constitute a particularly at-risk population. Mental health services for this group should not assume a natural post-pandemic recovery but instead be prepared to address persistently elevated levels of depression in the post-pandemic period.

Results also supported H2: Older adults with poorer baseline health—characterized by functional limitations, psychiatric problems, and poor self-rated health—experienced steeper increases in depressive symptoms during the outbreak stage, even as symptoms rose across the entire population. This supports the idea that COVID-19 acted as an "inequality amplifier," disproportionately intensifying distress among already disadvantaged groups [30–32]. Moreover, while disparities linked to functional and psychiatric limitations plateaued after 2020, those tied to poor self-rated health persisted through 2022. This finding implies that interventions should prioritize those with chronic health conditions or poor self-rated health, as they experienced compounded and persistent distress.

Findings for H3 indicate that although depressive symptoms stabilized at the population level between 2020 and 2022, this apparent plateau masked meaningful heterogeneity in post-outbreak trajectories. Disparities associated with functional limitations and pre-existing psychiatric conditions did not continue to widen after the initial shock. However, poor self-rated health prior to the pandemic remained a

significant predictor of continued increases in depressive symptoms, indicating a persistent and uneven mental health burden. This pattern suggests that the durable impact of COVID-19 was not evenly distributed: while average depressive symptoms no longer rose, older adults who already perceived themselves as unhealthy continued to experience worsening depressive symptoms.

The distinctive role of self-rated health in driving persistent disparity warrants further consideration. Unlike specific functional limitations or diagnosed psychiatric conditions, self-rated health reflects a holistic assessment of physical, emotional, and social well-being [33]. Individuals who perceive themselves as overall unhealthy may experience a pervasive sense of vulnerability that extends beyond discrete health problems. This generalized vulnerability may have made them particularly susceptible to the ongoing uncertainties and disruptions of the prolonged pandemic, including evolving health risks, social isolation, and the erosion of familiar routines and support systems. Moreover, poor self-rated health often encapsulates unmeasured health concerns and subjective distress that are not captured by objective health indicators, potentially reflecting a broader constellation of risk factors that continued to exact psychological costs throughout the pandemic's duration [34].

It should be noted that our analytical sample comprised relatively healthy individuals, as those in poorer health were more likely to have died or dropped out of the study before or during the COVID-19 outbreak. Insofar as less healthy individuals are likely to experience sharper increases in depressive symptoms during crisis outbreaks, this survival selection likely biases our estimates downward, meaning that the true extent of inequality amplification may be underestimated in our analyses.

To conclude, this study demonstrates that COVID-19 produced a persistent disruption in older adults' mental health, compounded by pre-existing health vulnerabilities. The findings highlight the need for equity-focused mental health strategies to promote resilience and well-being in future public health emergencies. Future research should extend these analyses as additional data become available to determine whether depressive symptoms eventually (and when) recover or remain elevated. More detailed

measures of digital engagement—capturing purpose, quality, and intensity of use—are also needed to assess how online interactions shape resilience. Finally, studies should identify protective factors, including social support, policy safety nets, virtual social interactions, and community cohesion, that potentially buffer against compounding disadvantages in crises.

References

1. Centers for Disease Control and Prevention (2022) Provisional COVID-19 deaths by sex and age

2. Hale T, Angrist N, Cameron-Blake E, others (2021) Variation in Government Responses to COVID-19. Nat Hum Behav 5:529–538

3. Li M, Luo Y (2023) COVID-19 and the Mental Health of Older Adults in the United States. Res Aging 45:637–658

4. Wettstein M, others (2022) Changes in Depression among Older Europeans during the COVID-19 Pandemic. Soc Sci Med 301:114945

5. Prati G, Mancini AD (2024) Trajectories of depressive symptoms and subjective well-being before and after the onset of the COVID-19 pandemic: Two six-year longitudinal studies. J Psychiatr Res 178:322–330. https://doi.org/10.1016/j.jpsychires.2024.08.024

6. Shandra CL (2018) Disability, Physical Impairment, and Mental Health among Older Adults. Soc Sci Med 211:134–141

7. Centers for Disease Control and Prevention (2020) Health, United States, 2020

8. Meeks S, others (2011) Functional Impairment and Depressive Symptoms among Older Adults. Aging Ment Health 15:664–673

9. Yang Y (2006) How Does Functional Disability Affect Depressive Symptoms in Late Life? The Role of Perceived Social Support and Psychological Resources. J Health Soc Behav 47:355–372. https://doi.org/10.1177/002214650604700404

10. Caputo J, Simon RW (2013) Physical limitation and emotional well-being: Gender and marital status variations. J Health Soc Behav 54:241–257. https://doi.org/10.1177/0022146513484766

11. Fried LE, others (2005) Disaster Exposure and Mental Health: A Review. Annu Rev Public Health 26:1–16

12. Norris FH, others (2002) 60,000 Disaster Victims Speak: Part I. An Empirical Review of the Empirical Literature, 1981–2001. Psychiatry 65:207–239

13. Sarrias M, Jara J (2020) Natural Disasters and Mental Health: Evidence from Chile. World Dev 128:104858

14. Paccagnella O, Pongiglione B (2022) Depression deterioration of older adults during the first wave of the COVID-19 outbreak in Europe. Soc Sci Med 299:114828. https://doi.org/10.1016/j.socscimed.2022.114828

15. Peng S, Roth AR (2021) Social isolation and loneliness before and during the COVID-19 pandemic: A longitudinal study of U.S. adults older than 50. J Gerontol B Psychol Sci Soc Sci 77:e185–e190. https://doi.org/10.1093/geronb/gbab068

16. van Tilburg TG (2021) Emotional, social, and existential loneliness before and during the COVID-19 pandemic: Prevalence and risk factors among Dutch older adults. J Gerontol B Psychol Sci Soc Sci 77:e179–e184. https://doi.org/10.1093/geronb/gbab101

17. Wettstein M, Nowossadeck S, Vogel C (2022) Well-being trajectories of middle-aged and older adults and the corona pandemic: No "COVID-19 effect" on life satisfaction, but increase in depressive symptoms. Psychol Aging 37:175–189. https://doi.org/10.1037/pag0000664

18. Galea S, Keyes KM, Lowe DR (2020) Population Health in the COVID-19 Era: A Framework for Understanding Psychological Impact. Am J Public Health 110:964–970

19. Gayman MD, Turner RJ, Cui M (2008) Physical Limitations and Depressive Symptoms: Exploring the Nature of the Association. J Gerontol Ser B 63:S219–S228. https://doi.org/10.1093/geronb/63.4.S219

20. Choi SL, Carr D, Namkung EH (2021) Physical disability and older adults' perceived food and economic insecurity during the COVID-19 pandemic. J Gerontol B Psychol Sci Soc Sci 77:e123–e133. https://doi.org/10.1093/geronb/gbab162

21. Ito T, Hirata-Mogi S, Watanabe T, et al (2021) Change of use in community services among disabled older adults during COVID-19 in Japan. Int J Environ Res Public Health 18:1148. https://doi.org/10.3390/ijerph18031148

22. Park K, Chamberlain B, Song Z, et al (2021) A double jeopardy: COVID-19 impacts on the travel behavior and community living of people with disabilities. Transp Res Part Policy Pract 156:24–35. https://doi.org/10.1016/j.tra.2021.12.008

23. Ferraro KF, Shippee TP (2009) Aging and Cumulative Inequality: How Does Inequality Get Under the Skin? The Gerontologist 49:333–343. https://doi.org/10.1093/geront/gnp034

24. Farina MP, Ailshire JA (2022) Sociodemographic and health status differences in delaying medical care during the COVID-19 pandemic among older adults: findings from the Health and Retirement Study. BMC Public Health 22:1720. https://doi.org/10.1186/s12889-022-14118-4

25. Garnett A, Pollock H, Floriancic N, et al (2024) Social Connectedness Between Family Caregivers and Older Adults Living in Long-Term Care Homes in the Context of COVID-19. Can J Aging Rev Can Vieil 43:33–44. https://doi.org/10.1017/S0714980823000351

26. Fisher GG, Ryan LH (2017) Overview of the Health and Retirement Study and introduction to the special issue. Work Aging Retire 4:1–9. https://doi.org/10.1093/workar/wax032

27. Lunde L-H, Pallesen S, Krangnes L, Nordhus IH (2010) Characteristics of Sleep in Older Persons With Chronic Pain: A Study Based on Actigraphy and Self-reporting. Clin J Pain 26:132–137. https://doi.org/10.1097/AJP.0b013e3181b61923

28. Heris CL, Kennedy M, Graham S, et al (2022) Key features of a trauma-informed public health emergency approach: A rapid review. Front Public Health 10:1006513. https://doi.org/10.3389/fpubh.2022.1006513

29. Morganstein JC, Ursano RJ (2020) Ecological Disasters and Mental Health: Causes, Consequences, and Interventions. Front Psychiatry 11:1. https://doi.org/10.3389/fpsyt.2020.00001

30. Dade M, Downing A, Benessaiah K, et al (2022) Inequalities in the adaptive cycle: reorganizing after disasters in an unequal world. Ecol Soc 27:art10. https://doi.org/10.5751/ES-13456-270410

31. Pierce M, Hope H, Ford T, et al (2020) Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population. Lancet Psychiatry 7:883–892. https://doi.org/10.1016/S2215-0366(20)30308-4

32. Thomas DSK, Jang S, Scandlyn J (2020) The CHASMS conceptual model of cascading disasters and social vulnerability: The COVID-19 case example. Int J Disaster Risk Reduct 51:101828. https://doi.org/10.1016/j.ijdrr.2020.101828

33. Idler EL, Benyamini Y (1997) Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies. J Health Soc Behav 38:21–37

34. Xiong J, Lipsitz O, Nasri F, et al (2020) Impact of COVID-19 pandemic on mental health in the general population: A systematic review. J Affect Disord 277:55–64. https://doi.org/10.1016/j.jad.2020.08.001

Table 1. Weighted Characteristics of Analytic Samples, Health and Retirement Study 2010-2022 (N=8,284).

	Mean ± SD or %
Functional Limitations (2018)	4.19 ± 4.41
Chronic Conditions (2018)	2.50 ± 1.65
Emotional/Psychiatric Problems (2018)	22.49
Self-rated Poor/Fair Health (2018)	25.24
Social Media Use Frequency (2014-18)	
Birth Cohort	
HRS (1931-41)	25.46
AHEAD/CODA (<=1930)	10.51
War Babies (1942-47)	18.26
Early Boomers (1948-53)	22.42
Mid Boomers (1954-59)	23.35
Male	46.05
Age (2020)	74.01 ± 9.98
Religious Attendance (2018)	2.67 ± 1.42
Race	
White	78
Black	10.02
Hispanic	8.57
Other	3.41
Years of Education	13.09 ± 3.17
Marital Status (2018)	
Married	57.44
Divorced/separated/widowed	35.98
Never married	6.58
Income (2016-18; in 1,000)	82.47 ± 132.41
Wealth (2016-18; in 10,000)	66.07 ± 152.46
Employed (2018)	29.8
Urbanicity (2018)	
Urban	49.99
Suburb	23.16
Rural	26.85
HRS 2020 Wave Interview Time	
March-May, 2020	24.85
June-Oct.2020	59.64
Nov.2020-May2021	15.51

Table 2. Factor loadings from the Normal Ogive Item Response Theory Model for the Latent State of Depressive Symptoms.

Indicators (yes/no) for Depressive Symptoms "Much of the time during the past week, ..."	**2010**	**2012**	**2014**	**2016**	**2018**	**2020**	**2022**
"...you felt depressed."	0.92	0.93	0.92	0.92	0.92	0.91	0.91
"...you felt that everything you did was an effort."	0.78	0.79	0.77	0.77	0.76	0.76	0.75
"…your sleep was restless."	0.63	0.64	0.62	0.61	0.61	0.61	0.59
"…you were happy." (reverse-coded)	0.87	0.88	0.86	0.86	0.86	0.86	0.85
"…you felt lonely."	0.82	0.83	0.81	0.81	0.81	0.80	0.79
"…you enjoyed life." (reverse-coded)	0.87	0.88	0.87	0.86	0.86	0.86	0.85
"…you felt sad."	0.88	0.89	0.87	0.87	0.87	0.87	0.86
"…you could not get going."	0.72	0.73	0.71	0.70	0.70	0.70	0.68

NOTE: A factor loading in the IRT model indicates how strongly an item could differentiate the population in terms of the latent trait of depressive symptoms. Although factor loadings were constrained to be equal across time, the standardized factor loadings may slightly vary due to small differences in cross-wave variances.

Table 3. Y-standardized regression coefficients for predictors of Latent Change Scores of Depressive Symptoms, Health and Retirement Study 2018-2022 (N=8,284)

	2018-2020 Change Score		2020-2022 Change Score	
	Beta	SE	Beta	SE
Functional Limitations	0.08***	0.01	-0.01	0.01
Chronic Conditions	0.07***	0.02	0.02	0.02
Emotional/Psychiatric Problems				
Self-rated Poor/Fair Health	0.35***	0.06	0.18***	0.06
Depressive Symptoms 2018	0.11	0.07		
Depressive Symptoms 2020			-0.12	0.08
Cohort				
HRS (1931-41)	Reference			
AHEAD/CODA (<=1930)	0.06	0.14	-0.05	0.14
War Babies (1942-47)	-0.02	0.09	-0.13	0.09
Early Boomers (1948-53)	-0.04	0.1	-0.18	0.12
Mid Boomers (1954-59)	-0.04	0.13	-0.11	0.15
Male	-0.19***	0.04	0.04	0.05
Age (2020)	-0.01*	0.01	0.00	0.01
Religious Attendance	-0.04*	0.02	-0.02	0.02
Race				
White	Reference			
Black	-0.13	0.07	0.09	0.09
Hispanic	0.13	0.08	0.02	0.07
Other	-0.04	0.13	0.04	0.18
Years of Education	0	0.01	-0.02	0.01
Marital Status				
Married	Reference			
Divorced/separated/widowed	0.14*	0.06	-0.09	0.07
Never married	0.34***	0.09	-0.07	0.14
Income (in 1,000)	-0.07*	0.03	-0.07*	0.03
Wealth (in 10,000)	0.01	0.01	0	0.01
Employed	-0.01	0.05	-0.03	0.06
Urbanicity				
Urban	Reference			
Suburb	-0.08	0.06	-0.06	0.05
Rural	-0.03	0.06	-0.03	0.07
HRS 2020 Wave Interview Time				
March-May, 2020	Reference			
June-Oct.2020	-0.08	0.05	0.09	0.06
Nov.2020-May2021	0.08	0.06	-0.01	0.07

* p < .05 ** p < .01 *** p < .001.

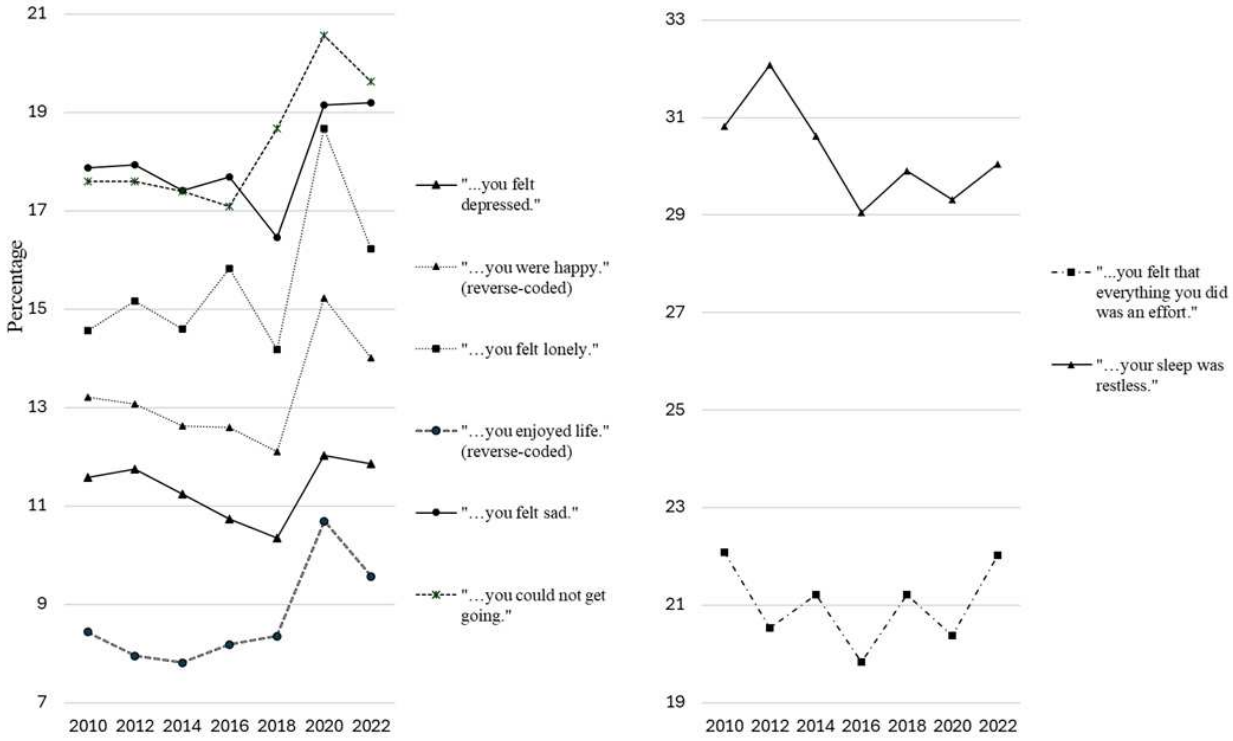


Figure 1. Temporal trend of observed indicators for depressive symptoms, 2010 - 2022.

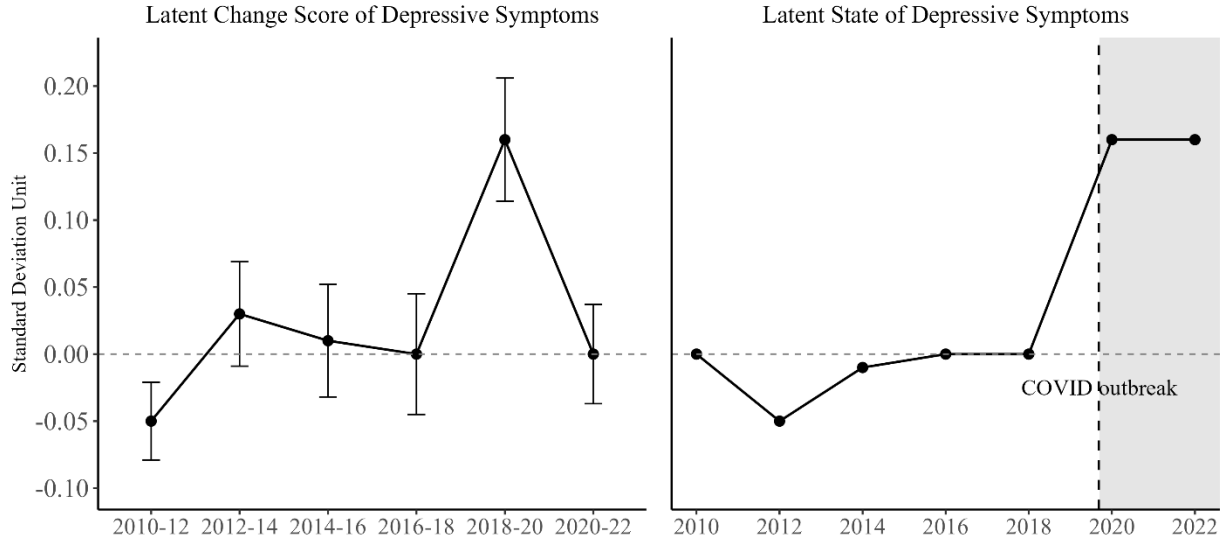


Figure 2. Predicted Latent Change Scores and State Scores of Depressive Symptoms, 2010-2022.

Appendix A. Technical Details on the Construction of Analytic Weights

This appendix details the procedures used to construct the analytic weights for Sample I and Sample II. The objective was to adjust for attrition, nonresponse, and missing data so that the final analytic samples remained representative of older U.S. adults born before 1960. Weighting involved three steps: (1) defining baseline survey weights, (2) propensity score adjustment for inclusion probability, and (3) post-stratification via iterative proportional fitting (raking). Propensity score models and raking were implemented in Stata.

A1. Baseline Weights

The baseline weight was defined as the 2010 HRS survey weight:

$$w_i^{(0)} = w_i^{\text{HRS2010}}$$

A2. Propensity Score Adjustment

Next, we estimated the probability of being included in the analytic sample using baseline demographic, socioeconomic, health, and behavioral characteristics. The model was specified as:

$$\Pr(S_i = 1 \mid X_i) = \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)}$$

where $S_i = 1$ indicates inclusion in the analytic sample and X_i includes predictors such as age, education, sex, race/ethnicity, health conditions, functional limitations, smoking/drinking, cognition, depressive symptoms, marital status, work status, household income and wealth, interview mode, and HRS cohort.

The inverse of the estimated propensity score was used to reweight included cases:

$$w_i^{(1)} = w_i^{(0)} \cdot \frac{1}{\hat{p}_i}$$

where $\hat{p}_i$ is the predicted inclusion probability. Extreme weights were trimmed at five times the mean weight to reduce instability.

A3. Post-Stratification (Raking)

Finally, the adjusted weights were calibrated to match the 2010 U.S. population benchmarks on key demographic and socioeconomic margins, using iterative proportional fitting (raking). The raking margins included:

- Sex (male/female)
- Race/ethnicity (White, Black, Hispanic, Other)
- Marital status (married/partnered, divorced/separated/widowed, never married)
- Birth cohort (AHEAD/CODA, HRS, War Babies, Early Boomers, Mid Boomers)
- Education (five categories of years of schooling)
- Employment status (working/not working)
- Urbanicity (urban, suburban, rural)
- Self-rated health (poor/fair vs. good/very good/excellent)

The raked weight for respondent i is given by:

$$w_i^{(2)} = w_i^{(1)} \cdot \prod_{k=1}^{K} \frac{M_k}{\sum_{j \in C_k} w_j^{(1)}}$$

where M_k is the known population total for margin k, and the denominator is the weighted sum for the analytic sample in category C_k. Iterative proportional fitting was performed until convergence, ensuring that the weighted distributions of the analytic samples matched the 2010 U.S. benchmarks.

A4. Final Weights

The final analytic weights for the sample were thus constructed as:

$$w_i^* = w_i^{(2)}$$

These final weights combine: (a) baseline survey weights, (b) inverse-probability adjustment for inclusion, and (c) raking to 2010 U.S. benchmarks. They allow generalization of findings from the analytic samples to the population of U.S. adults born before 1960 while accounting for the HRS complex survey design (strata and primary sampling units).

Appendix B. Items on Functional Limitations, Health and Retirement Study 2010-2018.

Because of a health problem do you have any difficulty with … (Yes/No)

walking several blocks
walking one block
running or jogging about a mile
sitting for about two hours
getting up from a chair after sitting for long periods
climbing several flights of stairs without resting
climbing one flight of stairs without resting
stooping, kneeling, or crouching
reaching or extending your arms above shoulder level
pulling or pushing large objects like a living room chair
lifting or carrying weights over 10 pounds, like a heavy bag of groceries
picking up a dime from a table

Because of a health or memory problem do you have any difficulty with …(Yes/No)

dressing, including putting on shoes and socks
walking across a room
bathing or showering
eating, such as cutting up your food
getting in or out of bed
using the toilet, including getting up and down
preparing a hot meal
shopping for groceries
making phone calls
taking medications
managing your money, such as paying your bills and keeping track of expenses
using a map to figure out how to get around in a strange place

Appendix C. Latent Change Score Model Specification

We first examined latent change scores for each adjacent interval (2010–2012, 2012–2014, 2014–2016, 2016–2018, 2018–2020, and 2020–2022). The central test for H1 was whether the increase in depressive symptoms was significantly greater during 2018–2020 compared to earlier periods, consistent with a COVID-related disruption, and whether the subsequent 2020–2022 change was close to zero, suggesting plateauing at a higher level. The model can be written as:

$$P(Y_{ijt} = 1 \mid t_t) = \Phi(\lambda_j \cdot t_t + \tau_j)$$

$$t_{t+1} = t_t + \Delta_{\eta_{t,t+1}}$$

$$\Delta_{\eta_{t,t+1}} = \mu_{\Delta_{\eta_{t,t+1}}} + \gamma_t \cdot t_t + \zeta_{\Delta_{\eta_{t,t+1}}}$$

, where $Y_{ijt} \in \{0,1\}$ represents the j^{th} observed binary item response to the CESD-8 scale at time t for individual i; $\Phi(\cdot)$ the standard normal cumulative distribution function (CDF); λ_j the factor loading for item j (constrained invariant across time); τ_j the threshold for item j (constrained invariant across time); $t_t$and t_{t+1} the latent depressive symptoms scores at time t and $t+1$, respectively; $\Delta_{\eta_{t,t+1}}$ the latent change score of depressive symptoms from time t to time $t+1$; $\mu_{\Delta_{\eta_{t,t+1}}}$ intercept (mean) of the latent change score from time t to time $t+1$; γ_t coefficient of the previous wave's latent depressive symptom state in predicting the latent change score; and $\zeta_{\Delta_{\eta_{t,t+1}}} \sim N(0, \psi)$ the residual of $\Delta_{\eta_{t,t+1}}$.

In the model specification, the first equation represents the measurement model (which is essentially a normal ogive IRT model), and the subsequent two equations comprise the structural models. The measurement model specified scalar invariance over time, that is, factor loading and the intercept (i.e., threshold) for each item of the CESD-8 scale were constrained to be equal across time (hence, there is no subscript t to λ and τ). Such a specification was supported by a thorough measurement invariance test,

which compared the goodness-of-fit between the unconstrained and constrained models, and confirmed the superiority of the constrained model. Such a scalar invariance specification also ensures that latent scores of depressive symptoms across waves are measured on an identical scale and thus comparable. In the structural part, the $\mu_{\Delta_{\eta_{t,t+1}}}$ is the parameter of central interest, which is the model-predicted mean of the latent change score from time t to time $t+1$. We specified the autoregressive coefficient γ_t to reflect the realistic situation that changes between two waves are often influenced by the state level of the previous wave.

To test H2a and H3, which focused on health-based inequality amplification, we extended the above LCSM by adding health vulnerability variables as predictors for the latent change score in 2018-2020 (for testing H2a) and the latent change in 2020-2022 (for testing H2b) in one integrated model:

$$\begin{pmatrix}\Delta_{18,20}\\ \Delta_{20,22}\end{pmatrix} = \begin{pmatrix}\beta_0^{(1)}\\ \beta_0^{(2)}\end{pmatrix} + \mathbf{B}_{\text{health}}^{\mathsf{T}}\mathbf{X}_{\text{health}} + \mathbf{B}_{\text{cov}}^{\mathsf{T}}\mathbf{X}_{\text{cov}} + \begin{pmatrix}\zeta_{18,20}\\ \zeta_{20,22}\end{pmatrix}.$$

, where$\Delta_{18,20}$ and $\Delta_{20,22}$ respectively denote model estimated latent change scores for 2018-2020 and 2020-2022; $\mathbf{X}_{\text{health}} \in \mathbb{R}^{3\times 1}$ the column vectors of three health variables, $\mathbf{B}_{\text{health}} \in \mathbb{R}^{3\times 2}$ the coefficient matrix for health variables in predicting two latent change scores; and $(\zeta_{18,20}, \zeta_{20,22})'$ the residuals with mean zeros and freely estimated covariance $\text{Cov}(\zeta_{18,20}, \zeta_{20,22})$.