Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

American Journal of Infection Control 50 (2022) 482–490

Contents lists available at ScienceDirect

American Journal of Infection Control

journal homepage: www.ajicjournal.org

Major Article

Socio-demographic, lifestyle and health characteristics as predictors of self-reported Covid-19 history among older adults: 2006-2020 Health and Retirement Study

Hind A. Beydoun PhD, MPH [a,*], May A. Beydoun PhD, MPH [b], Sharmin Hossain PhD [b], Brook T. Alemu PhD [c], Rana S. Gautam PhD [d], Jordan Weiss PhD [e], Alan B. Zonderman PhD [b]

[a] Department of Research Programs, Fort Belvoir Community Hospital, Fort Belvoir, VA
[b] Laboratory of Epidemiology and Population Sciences, National Institute on Aging, NIA/NIH/IRP, Baltimore, MD
[c] Health Sciences Program, School of Health Sciences, Western Carolina University, Cullowhee, NC
[d] Department of Sociology and Human Services, University of North Georgia, Dahlonega, GA
[e] Department of Demography, UC Berkeley, Berkeley, CA

Key words:
Cardiometabolic
Coronavirus
Epidemiology
Older adults
Prediction

Background: To identify key socio-demographic, lifestyle, and health predictors of self-reported coronavirus disease 2019 (Covid-19) history, examine cardiometabolic health characteristics as predictors of self-reported Covid-19 history and compare groups with and without a history of Covid-19 on trajectories in cardiometabolic health and blood pressure measurements over time, among United States (U.S.) older adults.
Methods: Nationally representative longitudinal data on U.S. older adults from the 2006-2020 Health and Retirement Study were analyzed using logistic and mixed-effects logistic regression models.
Results: Based on logistic regression, number of household members (OR=1.26, 95% CI: 1.05, 1.52), depressive symptoms score (OR = 1.21, 95% CI: 1.04, 1.42) and number of cardiometabolic risk factors or chronic conditions ("1-2" vs "0") (OR = 0.27, 95% CI: 0.11, 0.67) were significant predictors of self-reported Covid-19 history. Based on mixed-effects logistic regression, several statistically significant predictors of Covid-19 history were identified, including female sex (OR = 3.06, 95% CI: 1.57, 5.96), other race (OR = 5.85, 95% CI: 2.37, 14.43), Hispanic ethnicity (OR = 2.66, 95% CI: 1.15, 6.17), number of household members (OR = 1.25, 95% CI: 1.10, 1.42), moderate-to-vigorous physical activity (1-4 times per month vs never) (OR = 0.38, 95% CI: 0.18, 0.78) and number of cardiometabolic risk factors or chronic conditions ("1-2" vs "0") (OR = 0.34, 95% CI: 0.19, 0.60).
Conclusions: Number of household members, depressive symptoms and number of cardiometabolic risk factors or chronic conditions may be key predictors for self-reported Covid-19 history among U.S. older adults. In-depth analyses are needed to confirm preliminary findings.

BACKGROUND

The World Health Organization labeled the coronavirus disease 2019 (Covid-19) triggered by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) as a public health emergency of international concern on January 30th, 2020[1] and as an infectious disease of pandemic magnitude on March 11th, 2020.[2-6] The ongoing Covid-19 pandemic has affected over 200 countries with approximately 131 million confirmed cases and 2.85 million fatalities by April 2021 worldwide, including 30.8 million confirmed cases and 555,000 fatalities in the United States alone.[3,6-11] The clinical presentation, course and prognosis of Covid-19 can range from asymptomatic to mild, moderate and severe symptomatology, potentially leading to

* Address correspondence to Hind A. Beydoun, PhD, MPH, Department of Research Programs, Fort Belvoir Community Hospital, 9300 DeWitt Loop, Fort Belvoir, VA 22060.
E-mail address: hind.a.baydoun.civ@mail.mil (H.A. Beydoun).
Funding/support: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The manuscript was supported in part by the Intramural Research Program of the National Institute on Aging in Baltimore, Maryland.
Conflicts of interest: None to report.
Disclaimer: The views expressed in this article are those of the authors and do not reflect the official policy of Fort Belvoir Community Hospital, the Defense Health Agency, Department of Defense, or the U.S. Government. Any discussion or mention of commercial products or brand names does not imply or support any endorsement by the Federal Government.
Availability of data and materials: The data generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

https://doi.org/10.1016/j.ajic.2022.02.021
0196-6553/Published by Elsevier Inc. on behalf of Association for Professionals in Infection Control and Epidemiology, Inc.

hospitalization, intensive care unit (ICU) admission and death.[4,6,11] Accumulating evidence from observational studies and meta-analyses has identified high-risk groups who may be more likely than others to experience the detrimental health consequences of Covid-19.[4,6,11-13]

The SARS-CoV-2 belongs to a family of coronaviruses (CoVs) which are positive- and single-stranded enveloped RNA viruses.[14,15] Several emerging infectious diseases identified in recent years had CoVs as their etiology including the 2002 severe acute respiratory syndrome coronavirus (SARS-CoV) which was responsible for 8,098 cases and 774 deaths in 26 countries[14,16] and the 2012 Middle East respiratory syndrome-Coronavirus (MERS-Cov) which was responsible for 2,449 cases and 845 deaths in 27 countries.[1,9,16] Research has established that individuals who are older, immunocompromised as well as those with cardiometabolic health problems or cardiorespiratory dysfunction are more susceptible to SARS-CoV, MERS-Cov and SARS-CoV-2 infection and their disease-specific complications.[9] A common feature of SARS-CoV and SARS-CoV-2 is their use of the angiotensin-converting enzyme 2 (ACE2) as a mechanism for cell entry causing the anti-inflammatory arm of renin−angiotensin −aldosterone system (RAAS), namely the ACE2-Angiotensin-(1−7)−Mas receptor (MasR) pathway, to be blocked, potentially leading to excessive inflammatory response.[15,16] The discovery that ACE2 plays a central role in SARS-CoV-2 infection and Covid-19 prognosis resulted in a controversy surrounding use of antihypertensive medications – especially angiotensin converting enzyme inhibitors (ACEi) and angiotensin II type I receptor blockers (ARB) which target the RAAS.[16] The ubiquity of ACE2, which can be expressed by a wide variety of cell and tissue types, has reinforced the idea that Covid-19 is not merely a respiratory condition while supporting the concept that cardiometabolic health, especially hypertension, is a key predictor of Covid-19 prognosis.[16,17] While ACE2 plays an important role in regulating the RAAS, evidence suggests that individuals diagnosed with hypertension express higher levels of ACE2 and are therefore more susceptible than others to deleterious effects of Covid-19.[11] A knowledge gap exists as to whether long-term exposure to biomarkers of hypertension, namely, systolic blood pressure (SBP), diastolic blood pressure (DBP) and mean arterial pressure (MAP) can predict Covid-19.

Previously conducted epidemiologic studies have contributed to a better understanding of the host characteristics that may influence susceptibility to Covid-19 infection and/or detrimental Covid-19 related outcomes for the purpose of risk stratification.[7-9] High-risk groups who are overrepresented among Covid-19 cases include men,[6-8,18] older adults,[6,7,15,16] minorities,[3,7,12] obese individuals[11,18] and those with pre-existing chronic conditions,[6,7,15,16] including hypertension,[3,6] diabetes,[3,11,14] coronary artery disease,[3,6,11,19] cerebrovascular disease,[2,3,6,11] arrhythmias,[11,13] heart failure,[3,6,11,20] chronic kidney disease,[12,18,20] chronic respiratory disease,[11,20] cancer[12,20] and multimorbidities.[12,18] These risk factors have been linked to a wide range of Covid-19 outcomes, including severity,[3,7,9,21,22] hospitalization,[2,4,11] Intensive Care Unit (ICU) admission,[3,6,10,11,16] mechanical ventilation[3,10,11,23] and mortality,[3,7,9,16] with evidence overwhelmingly generated using convenience samples within clinical settings.

The purpose of this cohort study involving a nationally representative sample of United States (U.S.) older adults from the 2006-2020 Health and Retirement Study (HRS) is 3-fold: (1) To identify key socio-demographic, lifestyle and health predictors of self-reported Covid-19 history; (2) To examine cardiometabolic health characteristics as predictors of self-reported Covid-19 history; (3) To compare groups with and without self-reported Covid-19 history on trajectories in cardiometabolic health and blood pressure measurements over time. The population-based nature and longitudinal design of the HRS enhance our ability to generalize study findings to older adults in the United States, while establishing a temporal relationship between cardiometabolic risk factors and Covid-19 outcomes.

MATERIALS AND METHODS

Data source

Initiated in 1992, the HRS is an ongoing, nationally representative longitudinal study of community-dwelling U.S. adults over the age of 50 and their spouses of any age. The HRS was designed to study economic well-being, labor force participation, health and family composition among older adults through biennial surveys administered by telephone or face-to-face interviews. Although the HRS only interviews community-dwelling adults in their baseline surveys, respondents who enter long-term care facilities are also retained. Multistage probability sampling of U.S. households within geographical strata was performed whereby African Americans, Hispanics, and residents of Florida were oversampled. Response rates at baseline and follow-up waves were >80% for all HRS interviews. Written informed consent was provided by all participants and the University of Michigan's Institutional Review Board approved study protocols. The HRS is sponsored by the National Institute on Aging (grant number U01AG009740) and the Social Security Administration. Details of HRS procedures were reported elsewhere.[24,25] This study was conducted in accordance with the Declaration of Helsinki and received a determination of research not involving human subjects at our institution.

Study participants

The original HRS study consists of participants from whom data were collected in 1992, 1994, and 1996, and the Study of Asset and Health Dynamics of the Oldest Old (AHEAD) consists of those from whom data were collected in 1993 and 1995. The two studies were merged and 2 new cohorts (the Children of the Depression (born 1924-1930) and the War Babies (1942-1947)) were added in 1998. Subsequently, the Early Baby Boomers (1948-1953) cohort was added in 2004, the Mid Baby Boomers (1954-1959) cohort was added in 2010 and the Late Baby Boomers (1960-1965) cohort was added in 2016. Starting in 2006, HRS began collecting data on psychosocial factors, whereby half of the sample completed detailed face-to-face interviews that included physical, biological, and psychosocial measures, and the other half completed a core interview by telephone. To reduce study-related costs and burden on participants, enhanced interviewing alternated between half-samples at each subsequent wave. Specifically, interviewers left behind a self-report psychological questionnaire at the end of each interview, and respondents returned the completed questionnaire by mail to the Institute for Social Research Survey Research Center at the University of Michigan. The response rate for the leave-behind questionnaire among interviewees was ∼90%. For the purpose of performing cross-sectional and longitudinal data analyses, our study sample was restricted to HRS participants with Covid-19 data collected during the 2020 HRS wave and socio-demographic, lifestyle and health characteristics collected during the 2006, 2008, 2010, 2012, 2014, 2016, 2018, and/or 2020 HRS waves. As part of the 2020 Covid-19 project, a previously selected enhanced face-to-face interviewing (EFTF) half-sample was interviewed by telephone due to social distancing restrictions. EFTF half-sample release to fieldwork occurred sequentially on June 11, 2020 (EFTF1) and September 24, 2020 (EFTF2). To achieve our study goals, we linked the latest release of the 2020 HRS Covid-19 project, which became publicly available for 3,266 EFTF respondents in February 2021 to the 1992-2018 HRS longitudinal file developed by the RAND Center for the Study of Aging.

Study variables

Covid-19 history

Self-reported Covid-19 history was defined as a dichotomous ("yes" or "no") variable among 2020 HRS participants based on an algorithm that combines responses to a series of questionnaire items focused on Covid-19 infection, symptoms and/or outcomes: ("Have you had or do you now have Covid-19, the disease caused by the novel coronavirus?" ["Yes"] OR ("Have you been tested for the coronavirus?" ["Yes"] AND "Did the test indicate that you had the virus?" ["Yes"]) OR ("Did a doctor or other health care provider tell you that you have the disease? ['Yes']") OR ("Did you have to go to an emergency room because of the virus?" ['Yes']) OR ("Were you admitted to a hospital because of the virus?" ["Yes"]) OR "Were you on oxygen or a ventilator while you were in the hospital?" ["Yes, Oxygen," "Yes, Ventilator," "Both"] OR (Have you experienced any lingering physical or mental health effects from the virus? ["Yes"]).

Socio-demographic characteristics

In 2006-2020 HRS data were extracted on sex (male, female), birth cohort (Original/AHEAD/Children of the Depression, War Babies, Early Baby Boomers, Mid Baby Boomers, Late Baby Boomers), age (continuous; 50-59, 60-69, 70-79, 80+ years), race (White/Caucasian, Black/African American, Other), ethnicity (Hispanic, non-Hispanic), marital status (never married, married/partnered, separated/divorced, widowed), education (No degree, GED, High school diploma, some college, college degree or higher), work status (working, not working), federal insurance coverage (Yes, No), total wealth (in U.S. dollars) (<25,000, 25,000–124,999, 125,000–299,999, 300,000+), number of household members (≤ 3, > 3) and Census region of residence (Northeast, Midwest, South, West).[26] Of these characteristics, sex, age and race/ethnicity are established risk factors for Covid-19. Furthermore, marital status, number of household members and region of residence were available with minimal amount of missing data until 2018, whereas other socio-demographic variables were available until 2020.

Lifestyle characteristics

In 2006-2020 HRS data were extracted on smoking status (never smoker, past smoker, current smoker), frequency of alcohol consumption (abstinent, 1-3 days per month, 1-2 days per week, ≥3 days per week) and frequency of moderate and vigorous exercise (never, 1-4 times per month, or >1 time per week). Of these characteristics, smoking and physical exercise are established Covid-19 risk factors.

Health characteristics

In 2006-2020 HRS data were extracted on self-rated health and depressive symptoms. Self-rated health was evaluated using a single item ("would you say your health is excellent, very good, good, fair, or poor?") and dichotomized as "excellent/very good/good" versus "fair/poor". Symptoms of depression were assessed using a modified 8-item Center for Epidemiological Studies Depression Scale (CES-D) and total CES-D score was calculated with higher scores indicating worse symptoms of depression.[25,27] Neither self-rated health nor symptoms of depression are established Covid-19 risk factors although both of these characteristics have been linked to morbidity or mortality risks.

Cardiometabolic health

Directly measured (until 2018) and self-reported (until 2020) weight and height measurements, as well as self-reported presence of obesity-related cardiometabolic risk factors and chronic conditions, were extracted from the 2006-2020 HRS waves of data. Body mass index (BMI) was defined as weight (in kilograms) divided by height (in meters) squared, and categorized as <25, 25-29.9, ≥30 kg/m^2. The presence of obesity-related cardiometabolic risk factors and chronic conditions was determined using a series of standard questions focused on physician-diagnosed hypertension, diabetes, heart disease (heart attack, coronary heart disease, angina, congestive heart failure and/or other heart problems) and stroke. We further categorized the number of obesity-related cardiometabolic risk factors and chronic conditions as "0," "1-2," and "≥ 3."[25,27]

Blood pressure measurements

The HRS documentation includes a "Physical Measures & Biomarkers Booklet" which describes standard procedures used for measuring blood pressure, breathing, head strength, balance tests (with 30 seconds full-tandem), balance tests (with 60 seconds full-tandem), walking test, height, weight, waist circumference (WC), among others, and for collecting biological (saliva, blood spot) specimens. During each of 2006, 2008, 2010, 2012, 2014, 2016, and 2018 HRS waves, SBP and DBP were determined 3 times – with 45 seconds to 1 minute between measurements – for each participant using a sphygmomanometer. After instructing participants to relax and remain seated, the researcher placed the cuff on the left arm that lay on a flat surface with the participant's palm facing upwards to ensure that the center of the upper arm was at the same height as the participant's heart. The researcher provided each participant their results after recording all 3 measurements in mm Hg. For each HRS wave and participant, average SBP and DBP were calculated based on triplicate measurements. Using these average values for SBP and DBP, we calculated a MAP based on the formula: MAP = (SBP + 2*DBP) / 3. At each HRS wave, a participant was identified as having hypertension if they had an average SBP > 140 mm Hg and/or an average DBP > 90 mm Hg. Data on SBP, DBP, and MAP for participants in the 2020 HRS Covid-19 project were collected during the 2008, 2012, and 2016 HRS waves of data.

Statistical analysis

Complete subject analyses were conducted using Stata release 16 (StataCorp19. Stata Statistical Software; Release 16. College Station: StataCorp LLC) while taking into account complex sampling design and using the preliminary HRS Covid-19 project weight variable *CVWGTR* to ensure national representativeness of estimates. Whereas categorical data were summarized using frequencies and percentages, continuous data were summarized by calculating measures of central tendency (mean, median) and dispersion (standard error [SEM], interquartile range), as appropriate. Furthermore, we examined bivariate associations using uncorrected Chi-square and design-based F-tests and performed predictive modeling using logistic and mixed-effects logistic regression modeling for binary outcomes. First, we described socio-demographic, lifestyle and health characteristics at the latest HRS wave of data according to self-reported Covid-19 history. Second, we constructed binary logistic regression models for associations of cardiometabolic health and blood pressure measurements at the latest HRS wave of data with self-reported Covid-19 history, before and after controlling for socio-demographic, lifestyle and health characteristics that were significantly related to self-reported Covid-19 history in bivariate analyses at $\alpha = 0.20$. Third, we displayed trajectories in cardiometabolic health and blood pressure measurements over time after stratifying by self-reported Covid-19 history. Specifically, we applied Locally Weighted Scatterplot Smoothing (LOWESS) using default STATA settings including a bandwidth of 0.8. The LOWESS is a nonparametric strategy for fitting a smooth curve to data points to find the optimally shaped curve without making any assumptions with respect to a theoretical distribution. Fourth, we constructed mixed-effects binary logistic regression models for repeated measures of cardiometabolic health characteristics, SBP, DBP, and MAP as predictors of self-reported Covid-19 history, before

and after controlling for socio-demographic, lifestyle and health characteristics that were significantly related to self-reported Covid-19 history in bivariate analyses at $\alpha = 0.20$. Finally, we constructed logistic and mixed-effects logistic regression models for key predictors of self-reported Covid-19 history. We performed two-sided statistical tests while assuming an alpha level of 0.05.

RESULTS

As shown in Figure 1, 17,132 out of 42,233 HRS participants were ≥ 50 years of age at the 2006, 2008, 2010, 2012, 2014, 2016, or 2018 waves of data. Of those, 2,931 HRS participants took part in the 2020 Covid-19 project. Whereas 2,874 of these HRS participants had no missing data on Covid-19 infection, symptoms and/or outcomes used to define Covid-19 history, 2,830 remained after excluding those with no predictor variables from at least one of the 2006-2020 HRS waves. Accordingly, sub-samples of the 2,830 HRS participants were used for mixed-effects modeling as well as analyses involving data from the 2020 Covid-19 project alone.

Table 1 presents socio-demographic, lifestyle, and health characteristics at the latest wave of data according to self-reported Covid-19 history. Whereas the overall prevalence of Covid-19 history was 1.1%, age was inversely related to Covid-19 history (OR = 0.93, 95% CI: 0.88, 0.98), and "Late Baby Boomers" were significantly more likely than those belonging to the "Original/AHEAD/Children of the Depression" cohorts to report history of Covid-19 (OR = 6.80, 95% CI: 1.59, 29.34). Similarly, a one-unit increase in the number of household members was associated with nearly 40% increased odds of Covid-19 history (OR = 1.38, 95% CI: 1.16, 1.63), and a one-unit increase in depressive symptoms score was associated with nearly 20% increased odds of Covid-19 history (OR = 1.23, 95% CI: 1.00, 1.50). Although sex, race, ethnicity, smoking status, and physical activity were associated with Covid-19 history at $\alpha = 0.2$, no clear trend was observed with other socio-demographic, lifestyle, and health characteristics. Furthermore, age, and birth cohort were strongly correlated and could potentially cause multicollinearity if included simultaneously in regression models. Accordingly, sex, age, race, ethnicity, number of household members, smoking status, physical activity, and depressive symptoms score were considered in the final analyses as described in Table 4.

Table 2 displays logistic regression models for cardiometabolic health and blood pressure measurements at the latest wave of data as predictors of Covid-19 history. Clearly, the number of cardiometabolic risk factors or chronic conditions was the only cardiometabolic health characteristic that was significantly associated with Covid-19 history, before (Model I) and after (Model II) controlling for key socio-demographic, lifestyle and health characteristics identified in Table 1. Compared to individuals with no history of hypertension, diabetes, heart disease and/or stroke, those who reported 1 or 2 of these cardiometabolic health problems had lower odds of Covid-19 history (Crude OR = 0.27, 95% CI: 0.09, 0.73; Adjusted OR = 0.28, 95% CI: 0.11, 0.69).

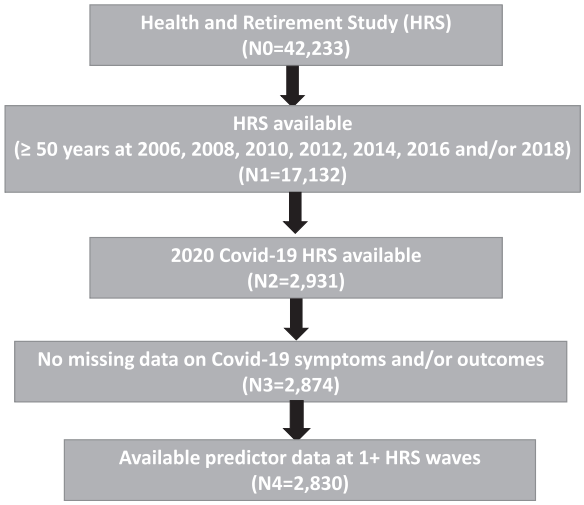

Fig 1. Study flowchart – 2006-2020 Health and Retirement Study.

Similarly, Table 3 displays mixed-effects logistic regression models for cardiometabolic health and blood pressure measurements as predictors of self-reported Covid-19 history, before (Model I) and after (Model II) controlling for key socio-demographic (sex, age, birth cohort, race, ethnicity, number of household members), lifestyle (smoking, physical activity) and health (depressive symptoms) characteristics identified in Table 1. Compared to individuals with no history of hypertension, diabetes, heart disease and/or stroke, those who reported 1 or 2 of these cardiometabolic health problems had lower odds of Covid-19 history in both Model I (Crude OR = 0.41, 95% CI: 0.25, 0.69) and Model II (Adjusted OR = 0.40, 95% CI: 0.24, 0.69). We did not observe statistically significant findings when examining specific cardiometabolic risk factors, chronic conditions or blood pressure measurements in relation to Covid-19 history.

Figures A.1-A.6 present trajectories in cardiometabolic risk factors and chronic conditions according to self-reported Covid-19 history. We did not observe any clear time trends in BMI or history of stroke when stratifying by Covid-19 history. By contrast, time trends in history of hypertension, diabetes and heart disease as well as number of cardiometabolic risk factors and/or chronic conditions differed between those with and without a history of Covid-19. Whereas those without a Covid-19 history had gradually increasing prevalence of these cardiometabolic health characteristics, trends among those with a history of Covid-19 were either U-shaped or J-shaped. Figures B.1-B.3 present trajectories between 3-time points (2008, 2012 and 2016) in blood pressure measurements according to Covid-19 history. A decreasing trend (2008-2012) followed by an increasing trend (2012-2016) in SBP and MAP were observed for individuals with a history of Covid-19, whereas linear trends were observed in the context of individuals without a history of Covid-19.

Table 4 displays a logistic regression model and a mixed effects logistic regression model for key predictors of self-reported Covid-19 history. These 2 models included sex, age, race, ethnicity, number of household members, smoking status, physical activity, depressive symptoms score as well as the number of cardiometabolic risk factors or chronic conditions. In Model I [logistic regression], number of household members (OR = 1.26, 95% CI: 1.05, 1.52), depressive symptoms score (OR = 1.21, 95% CI: 1.04, 1.42) and number of cardiometabolic risk factors or chronic conditions ("1-2" vs "0") (OR = 0.27, 95% CI: 0.11, 0.67) were statistically significant predictors of Covid-19 history. In Model II [mixed-effects logistic regression], several statistically significant predictors of Covid-19 history were identified, including female sex (OR = 3.06, 95% CI: 1.57, 5.96), other race (OR = 5.85, 95% CI: 2.37, 14.43), Hispanic ethnicity (OR = 2.66, 95% CI: 1.15, 6.17), number of household members (OR = 1.25, 95% CI: 1.10, 1.42), moderate-to-vigorous physical activity (1-4 times per month vs never) (OR = 0.38, 95% CI: 0.18, 0.78) and number of cardiometabolic risk factors or chronic conditions ("1-2" vs "0") (OR = 0.34, 95% CI: 0.19, 0.60).

DISCUSSION

To our knowledge, this is the first study to analyze data from a nationally representative sample of U.S. older adults for evaluating the longitudinal relationship between established Covid-19 prognostic factors and Covid-19 infection, symptoms and/or outcomes in a

Table 1
Socio-demographic, lifestyle and health characteristics at the latest wave of data according to self-reported Covid-19 history – 2020 Health and Retirement Study enhanced interviewing Covid-19 half-sample (n = 2,830)

	Total (N = 2,830)	Covid-19 history	
		% Yes	OR (95% CI)
OVERALL:		1.1	–
SOCIO-DEMOGRAPHIC:			
Sex:			*P* = .24
Male	46.4	0.8	Ref.
Female	53.5	1.4	1.89 (0.65, 5.40)
Age (y):			
			P = .01
Mean ± SEM	67.9 ± 0.2	–	0.93 (0.88, 0.98)
			P = .02
< 60	21.4	2.6	Ref.
60-69	40.1	1.0	0.39 (0.13, 1.21)
70-79	24.8	0.4	0.13 (0.02, 0.93)
≥ 80	13.7	0.4	0.15 (0.03, 0.64)
Birth cohort:			*P* = .02
Original/AHEAD/Children of the Depression	15.7	0.3	Ref.
War Babies	14.5	0.0	0.20 (0.02, 2.04)
Early Baby Boomers	20.1	0.7	2.08 (0.38, 11.35)
Mid Baby Boomers	24.1	1.4	4.04 (0.93, 17.67)
Late Baby Boomers	25.5	2.3	6.80 (1.59, 29.34)
Race:			*P* = .07
White / Caucasian	79.9	1.0	Ref.
Black / African American	10.9	0.6	0.62 (0.22, 1.76)
Other	9.2	2.7	2.68 (0.84, 8.57)
Ethnicity:			*P* = .04
Hispanic	9.9	0.9	2.53 (0.98, 6.53)
Non-Hispanic	90.1	2.4	Ref.
Education:			*P* = .08
No degree	10.5	0.9	Ref.
GED	5.3	0.7	0.69 (0.12, 3.75)
High school diploma	25.3	0.5	0.47 (0.12, 1.86)
Some college	28.2	0.9	0.86 (0.22, 3.38)
College degree or higher	30.6	2.0	2.09 (0.59, 7.31)
Marital status:			*P* = .49
Never married	6.3	0.7	Ref.
Married / Partnered	65.1	1.2	1.73 (0.38, 7.83)
Separated / Divorced	16.4	1.4	1.89 (0.36, 9.97)
Widowed	12.2	0.4	0.59 (0.11, 3.25)
Work status:			*P* = .94
Working	38.6	1.1	0.96 (0.33, 2.78)
Not working	61.4	1.1	Ref.
Federal health insurance coverage:			*P* = .32
Yes	65.1	0.9	0.58 (0.19, 1.72)
No	34.8	1.5	Ref.
Total wealth ($):			*P* = .86
< 25,000	24.1	1.4	Ref.
25,000-124,999	53.7	1.0	0.74 (0.24, 2.24)
≥ 125,000	22.1	1.0	0.74 (0.19, 2.96)
Number of household members:			
			P < .0001
Mean ± SEM	2.23 ± 0.03		1.38 (1.16, 1.63)
			P = .09
≤ 3	88.9	0.9	Ref.
> 3	11.1	2.3	2.39 (0.84, 6.84)
Census region of residence:			*P* = .16
Northeast	16.1	2.2	Ref.
Midwest	24.1	1.6	0.71 (0.16, 3.14)
South	38.4	0.7	0.32 (0.10, 0.99)
West	21.5	0.5	0.24 (0.07, 0.84)
LIFESTYLE:			
Smoking status:			*P* = .15
Never smoker	47.4	1.4	Ref.
Past smoker	40.8	0.6	0.40 (0.14, 1.16)
Current smoker	11.7	2.0	1.45 (0.39, 5.37)
Frequency of alcohol consumption:			*P* = .67
Abstinent	39.8	1.4	Ref.
1-3 d per mo	18.3	0.8	0.56 (0.12, 2.69)
1-2 d per wk	24.9	1.5	1.06 (0.29, 3.85)
≥3 d per wk	16.9	0.7	0.47 (0.12, 1.90)
Frequency of moderate / vigorous physical exercise:			*P* = .99
Never	15.8	1.2	Ref.
1-4 times per mo	23.7	1.1	0.98 (0.29, 3.32)
> 1 times per wk	60.4	1.1	0.97 (0.34, 2.75)
HEALTH:			
Self-rated health:			*P* = .64
Excellent/very good/good	75.2	1.2	Ref.
Fair/poor	24.8	0.9	0.78 (0.28, 2.21)
Depression symptoms score:			*P* = .04
Mean ± SEM	1.26 ± 0.05		1.23 (1.00, 1.50)

Abbreviations: AHEAD, Study of Asset and Health Dynamics of the Oldest Old; *CI*, Confidence interval; *OR*, Odds ratio; *SEM*, Standard Error of the Mean.

community setting. Nearly 1% of study participants self-reported a history of Covid-19 and multiple logistic regression models suggested that the number of household members and depressive symptoms score were consistently associated with increased likelihood of a history of Covid-19 whereas number of cardiometabolic risk factors or chronic conditions was consistently associated with a decreased likelihood of a history of Covid-19. Despite the fact that

Table 2
Logistic regression models for cardiometabolic health and blood pressure measurements at the latest wave of data as predictors of self-reported Covid-19 history before and after controlling for key socio-demographic, lifestyle and health characteristics – 2020 Health and Retirement Study enhanced interviewing Covid-19 half-sample (n = 2,830)

	Model I *		Model II†	
	OR	95% CI	OR	95% CI
CARDIOMETABOLIC HEALTH:				
Body mass index (kg/m²):				
Continuous	0.98	0.92, 1.03	0.96	0.88, 1.03
<25	Ref.	–	Ref.	–
25-29.9	0.63	0.19, 2.09	0.54	0.14, 2.13
≥30	0.90	0.22, 3.54	0.67	0.14, 3.22
Cardiometabolic risk factors and chronic conditions:				
Hypertension:				
Yes	0.48	0.18, 1.31	0.49	0.21, 1.14
No	Ref.	–	Ref.	–
Diabetes:				
Yes	0.59	0.18, 1.99	0.51	0.17, 1.51
No	Ref.	–	Ref.	–
Heart disease:				
Yes	0.86	0.29, 2.52	1.18	0.48, 2.85
No	Ref.	–	Ref.	–
Stroke:				
Yes	0.42	0.09, 1.79	0.49	0.11, 2.18
No	Ref.	–	Ref.	–
Number of conditions:				
0	Ref.	–	Ref.	–
1-2	0.27	0.09, 0.73	0.28	0.11, 0.69
≥ 3	0.56	0.11, 2.84	0.54	0.16, 1.91
BLOOD PRESSURE:				
SBP	0.99	0.97, 1.03	1.00	0.98, 1.03
SBP > 140 mm Hg	0.58	0.10, 3.25	0.75	0.16, 3.44
DBP	1.01	0.98, 1.05	1.01	0.97, 1.05
DBP > 90 mm Hg	0.58	0.13, 2.57	0.49	0.09, 2.61
MAP	1.00	0.97, 1.04	1.01	0.97 1.04

* Model I is unadjusted;
† Model II is adjusted for key socio-demographic, lifestyle and health characteristics. *Abbreviations: CI*, Confidence interval; *DBP*, Diastolic blood pressure; *MAP*, Mean arterial pressure; *OR*, Odds ratio; *SBP*, Systolic blood pressure.

Table 3
Mixed effects logistic regression models for cardiometabolic health and blood pressure measurements as predictors of self-reported Covid-19 history before and after controlling for socio-demographic, lifestyle and health characteristics – 2020 Health and Retirement Study enhanced interviewing Covid-19 half-sample (n = 2,830)

	Model I *		Model II†	
	OR	95% CI	OR	95% CI
CARDIOMETABOLIC HEALTH:				
Body mass index (kg/m^2):				
Continuous	0.98	0.94, 1.02	0.96	0.91, 1.01
<25	Ref.	–	Ref.	–
25-29.9	0.69	0.33, 1.41	0.64	0.28, 1.46
≥30	1.27	0.62, 2.59	1.04	0.49, 2.20
Cardiometabolic risk factors and chronic conditions:				
Hypertension:				
Yes	0.77	0.47, 1.27	0.74	0.45, 1.22
No	Ref.	–	Ref.	–
Diabetes:				
Yes	0.86	0.41, 1.79	0.69	0.31, 1.56
No	Ref.	–	Ref.	–
Heart disease:				
Yes	1.12	0.61, 2.06	1.35	0.68, 2.66
No	Ref.	–	Ref.	–
Stroke:				
Yes	1.16	0.57, 2.33	1.74	0.79, 3.81
No	Ref.	–	Ref.	–
Number of conditions:				
0	Ref.	–	Ref.	–
1-2	0.41	0.25, 0.69	0.40	0.24, 0.69
≥ 3	1.54	0.69, 3.44	1.66	0.70, 3.90
BLOOD PRESSURE:				
SBP	0.97	0.94, 1.00	0.99	0.96, 1.02
SBP > 140 mm Hg	0.29	0.08, 1.01	0.51	0.14, 1.78
DBP	0.99	0.96, 1.03	0.99	0.96, 1.04
DBP > 90 mm Hg	0.74	0.19, 2.87	0.80	0.23, 2.77
MAP	0.98	0.95, 1.01	0.99	0.96, 1.03

* Model I is unadjusted;
†Model II is adjusted for key socio-demographic, lifestyle and health characteristics.
Abbreviations: CI, Confidence interval; *DBP*, Diastolic blood pressure; *MAP*, Mean arterial pressure; *OR*, Odds ratio; *SBP*, Systolic blood pressure.

Table 4
Logistic regression and mixed effects logistic regression models for key predictors of self-reported Covid-19 history – 2020 Health and Retirement Study enhanced interviewing Covid-19 half-sample (n = 2,830)

	Model I *		Model II†	
	OR	95% CI	OR	95% CI
Sex:				
Male	Ref.	–	Ref.	–
Female	1.75	0.59, 5.10	3.06	1.57, 5.96
Age (y):				
Race:	0.96	0.91, 1.02	0.96	0.93, 0.99
White / Caucasian	Ref.	–	Ref.	–
Black / African American	0.62	0.22, 1.75	1.07	0.52, 2.20
Other	1.66	0.44, 6.18	5.85	2.37, 14.43
Ethnicity:				
Hispanic	1.67	0.59, 4.68	2.66	1.15, 6.17
Non-Hispanic	Ref.	–	Ref.	–
Number of household members:	1.26	1.05, 1.52	1.25	1.10, 1.42
Smoking status:				
Never smoker	Ref.	–	Ref.	–
Past smoker	0.49	0.18, 1.38	1.71	0.96, 3.04
Current smoker	1.14	0.31, 4.26	1.69	0.79, 3.59
Frequency of moderate / vigorous physical exercise:				
Never	Ref.	–	Ref.	–
1-4 times per mo	0.96	0.27, 3.46	0.38	0.18, 0.78
> 1 times per wk	0.91	0.30, 2.72	0.57	0.32, 1.01
Depression symptoms score:	1.21	1.04, 1.42	1.12	1.00, 1.25
Number of conditions:				
0	Ref.	–	Ref.	–
1-2	0.27	0.11, 0.67	0.34	0.19, 0.60
≥ 3	0.58	0.16, 2.08	1.55	0.65, 3.69

* Model I is logistic regression;
†Model II is mixed effects logistic regression.
Abbreviations: CI, Confidence interval; *DBP*, Diastolic blood pressure; *MAP*, Mean arterial pressure; *OR*, Odds ratio; *SBP*, Systolic blood pressure.

immunosenescence is known to mediate the impact of aging on Covid-19 susceptibility,[13] chronological age did not predict Covid-19 history among study participants after controlling for confounders. This study finding could be attributed to homogeneity of the population in terms of chronological age distribution.

Although individual and household-level data linking depressive symptoms and overcrowding to Covid-19 history may be limited, the global literature has established that the Covid-19 pandemic itself may be associated with a greater level of depressive symptoms among adults[28-30] and that its trajectory may be influenced by overcrowding[31-33] potentially worsening health disparities according to race, ethnicity and socioeconomic status.[12] Whereas depressive symptoms may be manifestations of stress, which in turn, could adversely affect immune response against microorganisms, including SARS-CoV-2, overcrowding may increase the opportunity for SARS-CoV-2 exposure potentially leading to a greater frequency of Covid-19 as the number of household members residing with older adults increases.

This study found an inverse relationship between the number of cardiometabolic risk factors or chronic conditions and Covid-19 history. This finding is in contrast to multiple systematic reviews and meta-analyses that have linked various Covid-19 outcomes to obesity and its associated cardiometabolic disorders.[1,6,34] However, it may be explained by the fact that study participants who completed 2020 HRS surveys are survivors of the Covid-19 pandemic who were asked to self-report Covid-19 infection, symptoms and/or outcomes used to define Covid-19 history. Therefore, it is likely that study participants with pre-existing health problems linked to worse Covid-19 outcomes may have taken precautions to reduce their exposure to Covid-19 and were, therefore, less likely than others to experience Covid-19. Shortly after onset of the Covid-19 pandemic, it was widely reported in the media that older adults with cardiometabolic risk may be more severely affected by the disease. It is therefore likely that the message has reached HRS participants. It is worth noting that, a year later, the emphasis on vaccinating the most vulnerable populations also highlighted the necessity for some individuals to take precautions.

Inconsistent with the published literature,[7,10,16] this study found a significant association between Covid-19 history and number of cardiometabolic features, but not with BMI categories or specific cardiometabolic features or blood pressure measurements. In a prospective cohort study of 5,795 hospitalized patients, aged 18 to 79 years, with confirmed SARS-CoV-2 infection, Czernichow et al. reported significantly higher mortality rates among obese patients as compared to those with BMI (18.5-25 kg/m^2), as follows: BMI (30-35 kg/m^2: OR = 1.89 (95% CI: 1.45, 2.47), 35-40 kg/m^2: OR = 2.79 (95% CI: 1.95, 3.97) and > 40 kg/m^2: OR = 2.55 (95% CI: 1.62, 3.95).[10] Aung et al. applied 1-sample and 2-sample Mendelian Randomization (MR) – using genetic risk scores – to evaluate obesity traits (BMI, WC) and cardiometabolic parameters (SBP, serum glucose, serum glycated hemoglobin [HbA1c], low-density lipoprotein [LDL] cholesterol, high-density lipoprotein [HDL] cholesterol and triglycerides [TG]) in relation to SARS-CoV-2 positivity in the UK Biobank cohort.[7] Based on 1-sample MR analyses, there was a direct causal relationship between genetically determined BMI and LDL cholesterol and Covid-19 risk (OR = 1.15, 95% CI: 1.05-1.26 and OR: 1.58, CI: 1.21-2.06, per 1

standard deviation increment in BMI and LDL cholesterol respectively), with similar findings for 2-sample MR analyses.[7] The absence of a significant association between specific cardiometabolic health characteristics and Covid-19 history may be attributed to sample size limitations or to prevalence-incidence bias whereby survivors of the Covid-19 pandemic were surveyed and those who self-reported a history of Covid-19 differed from those who did not have the opportunity to participate in the Covid-19 project as a result of death or disability. On the other hand, the distinct trends in diabetes, hypertension and heart disease as well as blood pressure measurements between those with and without a Covid-19 history necessitate further evaluation.

The HRS is a large, nationally representative study with > 20 years of longitudinal data covering several cohorts and it includes a wide range of socio-demographic, lifestyle and health-related markers. Nevertheless, study findings need to be interpreted with caution and in light of several limitations. First, the linkage of 2006-2018 HRS with 2020 HRS Covid-19 project data and missing information on key variables yielded analytic samples that were much smaller than the full HRS sample potentially leading to selection bias. When comparing potentially study-eligible HRS participants who were included in the study sample to those excluded from the study sample, differences were observed according to sex, but not according to birth cohort, race, ethnicity and level of education (Table C.1). Small sample sizes may also explain the wide confidence intervals around measures of association and the disparate findings of "1-2" versus "0" and "≥3" versus "0" cardiometabolic conditions in relation to Covid-19 history. A larger sample size is needed to clarify these findings, especially that more compromised adults from the HRS may not have taken part in the 2020 Covid-19 project. Second, the majority of HRS data were self-reported, potentially leading to nondifferential misclassification and measures of association that are biased towards the null value. Furthermore, the method of survey administration varied between the 2006-2018 HRS waves (face-to-face) versus the 2020 HRS wave (telephone), potentially affecting the quality of survey data. Unlike previously conducted studies, Covid-19 history was defined on the basis of self-reported infection, symptoms and/or outcomes, and did not incorporate data obtained from electronic health records or the National Death Index. Third, cross-sectional and longitudinal data analyses have been conducted using observational HRS data and, as such, the estimated relationships are prone to confounding bias and cannot be deemed causal. Given the observational design, there is a potential for reverse causality or endogeneity bias, especially when interpreting the correlation between depressive symptoms and Covid-19 history. Finally, this study involves secondary analysis of existing HRS data and topics consistently covered by the 2006-2020 waves of HRS data may or may not have yielded the most relevant predictors of Covid-19 history.

CONCLUSIONS

In conclusion, we identified number of household members, depressive symptoms, and number of cardiometabolic risk factors or chronic conditions as key predictors for self-reported Covid-19 history among U.S. older adults. These findings are consistent with the global literature on overcrowding as well as recommendations for Covid-19 preventive strategies which include regulation of cardiometabolic disease, discontinuation of smoking, a healthy, balanced diet, safe physical exercise, minimizing stress, maintaining adequate sleep, and reducing high alcohol intake.[9] In-depth analyses and larger sample sizes are needed to confirm these preliminary findings.

APPENDIX A

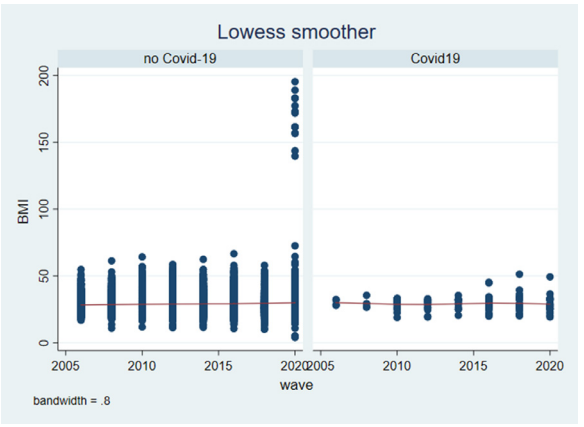

Fig A.1. Trajectories in body mass index according to presence of Covid-19 history.

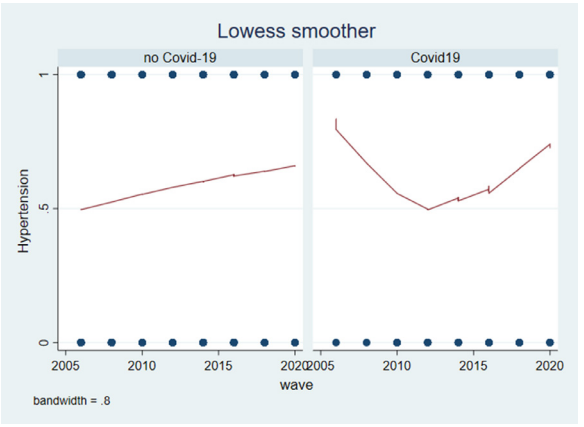

Fig A.2. Trajectories in hypertension according to presence of Covid-19 history.

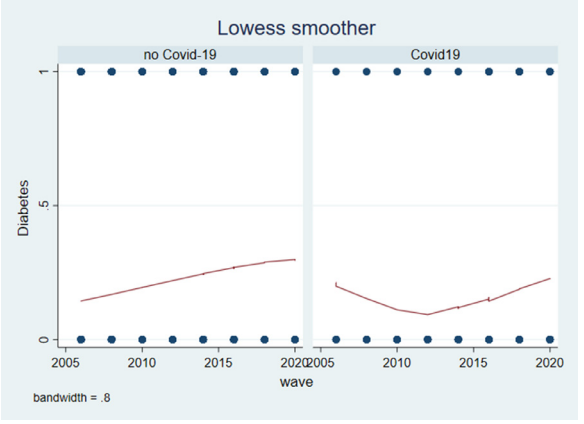

Fig A.3. Trajectories in diabetes according to presence of Covid-19 history.

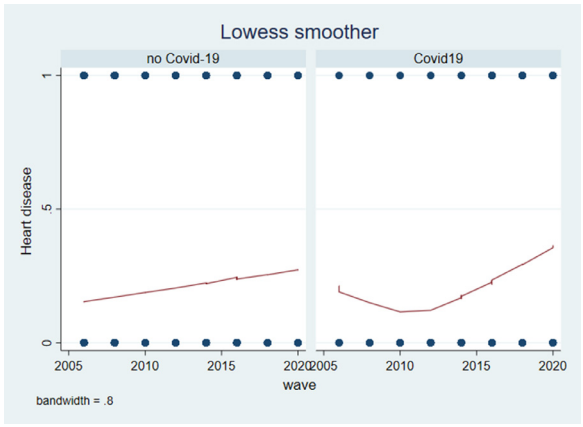

Fig A.4. Trajectories in heart disease according to presence of Covid-19 history.

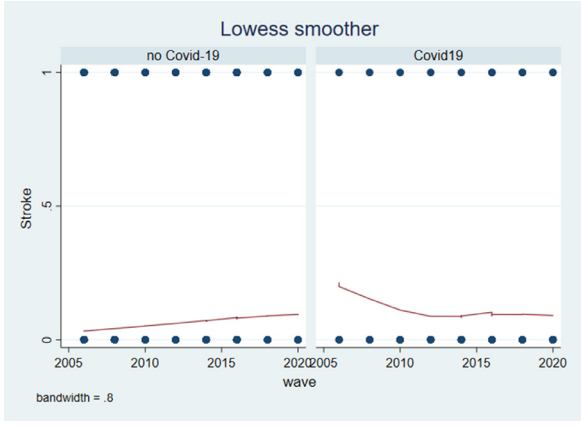

Fig A.5. Trajectories in stroke according to presence of Covid-19 history.

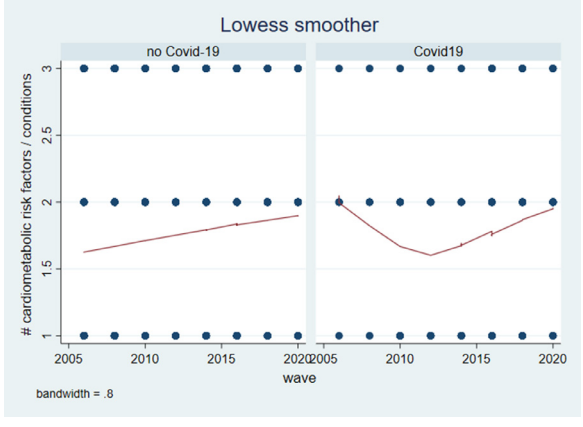

Fig A.6. Trajectories in number of cardiometabolic risk factors and chronic conditions according to presence of Covid-19 history.

APPENDIX B

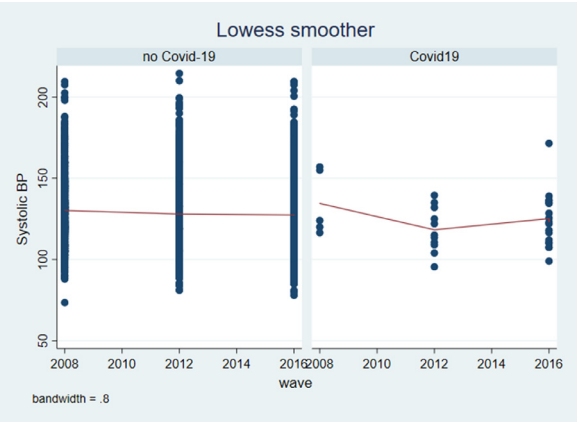

Fig B.1. Trajectories in systolic blood pressure according to presence of Covid-19 history.

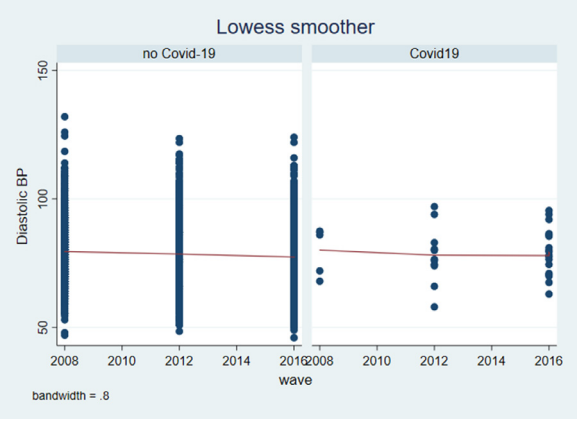

Fig B.2. Trajectories in diastolic blood pressure according to presence of Covid-19 history.

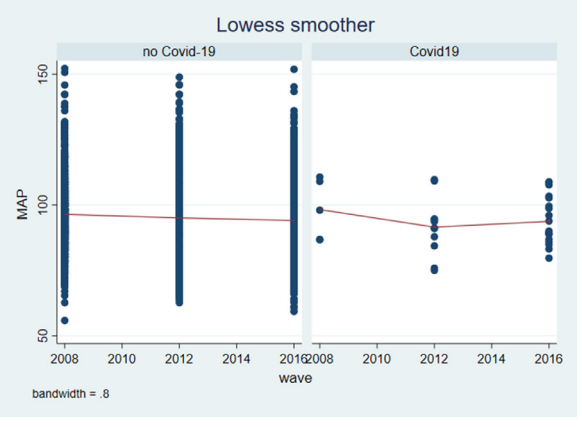

Fig B.3. Trajectories in mean arterial pressure according to presence of Covid-19 history.

APPENDIX C

Table C.1
Comparison of potentially eligible study participants (n = 2,874) and nonparticipants (n = 14,258) according to selected baseline characteristics – 2006-2020 Health and Retirement Study (n = 17,132)

	Study participants (%)	Study nonparticipants (%)	P*
Sex:			.0006
Male	46.4	72.6	
Female	53.6	27.4	
Birth cohort:			.16
Original/AHEAD/Children of the Depression	15.6	5.1	
War Babies	14.5	24.4	
Early Baby Boomers	20.1	27.5	
Mid Baby Boomers	24.2	20.4	
Late Baby Boomers	25.6	22.6	
Race:			.94
White / Caucasian	79.6	79.5	
Black / African American	10.9	9.9	
Other	9.5	10.6	
Ethnicity:			.44
Hispanic	10.2	7.1	
Non-Hispanic	89.7	92.9	
Education:			.73
No degree	10.9	10.2	
GED	5.3	4.2	
High school diploma	25.2	23.2	
Some college	27.9	21.9	
College degree or higher	30.6	40.5	

*P values were calculated based on design-based F tests.

References

1. Liu H, Chen S, Liu M, Nie H, Lu H. Comorbid chronic diseases are strongly correlated with disease severity among COVID-19 patients: a systematic review and meta-analysis. *Aging Dis*. 2020;11:668–678.
2. Kadosh BS, Garshick MS, Gaztanaga J, et al. COVID-19 and the heart and vasculature: novel approaches to reduce virus-induced inflammation in patients with cardiovascular disease. *Arterioscler Thromb Vasc Biol*. 2020;40:2045–2053.
3. Koliaki C, Tentolouris A, Eleftheriadou I, Melidonis A, Dimitriadis G, Tentolouris N. Clinical management of diabetes mellitus in the era of COVID-19: practical issues, peculiarities and concerns. *J Clin Med*. 2020;9.
4. Mechanick JI, Carbone S, Dickerson RN, et al. Clinical nutrition research and the COVID-19 pandemic: a scoping review of the ASPEN COVID-19 Task Force on Nutrition Research. *JPEN J Parenter Enteral Nutr*. 2020.
5. Piskorz D, Puente Barragan A, Lopez Santi R, et al. Psychological impact of the pandemic on ambulatory cardiometabolic patients without evidence of SARS-CoV-2 infection. The CorCOVID Latam Psy study. *Curr Probl Cardiol*. 2020;46:100737.
6. Tian W, Jiang W, Yao J, et al. Predictors of mortality in hospitalized COVID-19 patients: a systematic review and meta-analysis. *J Med Virol*. 2020;92:1875–1883.
7. Aung N, Khanji MY, Munroe PB, Petersen SE. Causal inference for genetic obesity, cardiometabolic profile and COVID-19 susceptibility: a mendelian randomization study. *Front Genet*. 2020;11:586308.
8. Bienvenu LA, Noonan J, Wang X, Peter K. Higher mortality of COVID-19 in males: sex differences in immune response and cardiovascular comorbidities. *Cardiovasc Res*. 2020;116:2197–2206.
9. Chowdhury R, van Daalen KR, Franco OH. Cardiometabolic health: key in reducing adverse COVID-19 outcomes. *Global Heart*. 2020;15:58.
10. Czernichow S, Beeker N, Rives-Lange C, et al. Obesity doubles mortality in patients hospitalized for severe acute respiratory syndrome coronavirus 2 in Paris hospitals, France: a cohort study on 5,795 patients. *Obesity*. 2020;28:2282–2289.
11. Dhindsa D, Wong ND, Sperling L. Cardiovascular and cardiometabolic prevention: high-level priority in the era of COVID-19. *Cardiovasc Endocrinol Metabol*. 2020;9:125–127.
12. Highton PJ, Hadjiconstantinou M, Schreder S, Seidu S, Davies M, Khunti K. COVID-19, ethnicity and cardiometabolic disease self-management in UK primary care. *Diabetes Metab Syndr*. 2020;14:2241–2243.
13. Saban-Ruiz J, Ly-Pen D. COVID-19: a personalized cardiometabolic approach for reducing complications and costs. The role of Aging beyond topics. *J Nutr Health Aging*. 2020;24:550–559.
14. Ramos-Lopez O, Daimiel L, Ramirez de Molina A, Martinez-Urbistondo D, Vargas JA, Martinez JA. Exploring host genetic polymorphisms involved in SARS-CoV infection outcomes: implications for personalized medicine in COVID-19. *Int J Genomics*. 2020;2020:6901217.
15. Cippa PE, Cugnata F, Ferrari P, et al. A data-driven approach to identify risk profiles and protective drugs in COVID-19. *Proc Natl Acad Sci U S A*. 2021;118.
16. de Lucena TMC, da Silva Santos AF, de Lima BR, de Albuquerque Borborema ME, de Azevedo Silva J. Mechanism of inflammatory response in associated comorbidities in COVID-19. *Diabetes Metab Syndr*. 2020;14:597–600.
17. El-Sayed Moustafa JS, Jackson AU, Brotman SM, et al. ACE2 expression in adipose tissue is associated with COVID-19 cardio-metabolic risk factors and cell type composition. medRxiv: the preprint server for health sciences. 2020.
18. McQueenie R, Foster HME, Jani BD, et al. Multimorbidity, polypharmacy, and COVID-19 infection within the UK Biobank cohort. *PloS One*. 2020;15:e0238091.
19. Rodilla E, Saura A, Jimenez I, et al. Association of hypertension with all-cause mortality among hospitalized patients with COVID-19. *J Clin Med*. 2020;9.
20. Bello-Chavolla OY, Bahena-Lopez JP, Antonio-Villa NE, et al. Predicting mortality due to SARS-CoV-2: a mechanistic score relating obesity and diabetes to COVID-19 outcomes in Mexico. *J Clin Endocrinol Metab*. 2020;105.
21. Maddaloni E, D'Onofrio L, Alessandri F, et al. Cardiometabolic multimorbidity is associated with a worse Covid-19 prognosis than individual cardiometabolic risk factors: a multicentre retrospective study (CoViDiab II). *Cardiovasc Diabetol*. 2020;19:164.
22. Raisi-Estabragh Z, McCracken C, Bethell MS, et al. Greater risk of severe COVID-19 in Black, Asian and Minority Ethnic populations is not explained by cardiometabolic, socioeconomic or behavioural factors, or by 25(OH)-vitamin D status: study of 1326 cases from the UK Biobank. *J Public Health*. 2020;42:451–460.
23. Mechanick JI, Rosenson RS, Pinney SP, Mancini DM, Narula J, Fuster V. Coronavirus and cardiometabolic syndrome: JACC focus seminar. *J Am Coll Cardiol*. 2020;76:2024–2035.
24. McGrath R, Vincent BM, Hackney KJ, Robinson-Lane SG, Downer B, Clark BC. The longitudinal associations of handgrip strength and cognitive function in Aging Americans. *J Am Med Dir Assoc*. 2019.
25. Hunter JC, Handing EP, Casanova R, et al. Neighborhoods, sleep quality, and cognitive decline: Does where you live and how well you sleep matter? *Alzheimer's & dementia: j Alzheimer's Assoc*. 2018;14:454–461.
26. Kaufmann CN, Mojtabai R, Hock RS, et al. Racial/ethnic differences in insomnia trajectories among U.S. older adults. *Am J Geriatr Psychiatry*. 2016;24:575–584.
27. Kim ES, Hershner SD, Strecher VJ. Purpose in life and incidence of sleep disturbances. *J Behav Med*. 2015;38:590–597.
28. Aihara Y, Kiyoshi M. Depressive symptoms in community-dwelling older adults in Japan before and during the COVID-19 pandemic. *Int J Geriatr Psychiatry*. 2021;36:1122–1123.
29. Schmitt Jr. AA, Brenner AM, Primo de Carvalho Alves L, Claudino FCA, Fleck MPA, Rocha NS. Potential predictors of depressive symptoms during the initial stage of the COVID-19 outbreak among Brazilian adults. *J Affect Disord*. 2021;282:1090–1095.
30. Vahratian A, Blumberg SJ, Terlizzi EP, Schiller JS. Symptoms of anxiety or depressive disorder and use of mental health care among adults during the COVID-19 pandemic - United States, August 2020-February 2021. *MMWR Morb Mortal Wkly Rep*. 2021;70:490–494.
31. Chen JT, Krieger N. Revealing the unequal burden of COVID-19 by income, race/ethnicity, and household crowding: US county versus zip code analyses. *Journal of Public Health Management and Practice: JPHMP*. 2021;27(Suppl 1). COVID-19 and Public Health: Looking Back, Moving Forward:S43-S56.
32. Kim YJ, Kang SW. Perceived crowding and risk perception according to leisure activity type during COVID-19 using spatial proximity. *Int J Environ Res Public Health*. 2021;18.
33. Zhang Z, Zeb A, Alzahrani E, Iqbal S. Crowding effects on the dynamics of COVID-19 mathematical model. *Advances in Difference Equations*. 2020;2020:675.
34. Singh AK, Gillies CL, Singh R, et al. Prevalence of co-morbidities and their association with mortality in patients with COVID-19: a systematic review and meta-analysis. *Diabetes Obes Metab*. 2020;22:1915–1924.