From financial wealth shocks to ill-health: allostatic load and overload

French, D. (2023). From financial wealth shocks to ill-health: allostatic load and overload. *Health Economics*, *32*(4), 939-952. https://doi.org/10.1002/hec.4648

Published in:
Health Economics

Document Version:
Publisher's PDF, also known as Version of record

Queen's University Belfast - Research Portal:
Link to publication record in Queen's University Belfast Research Portal

Publisher rights
Copyright 2023 the authors.
This is an open access article published under a Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution and reproduction in any medium, provided the author and source are cited.

General rights
Copyright for the publications made accessible via the Queen's University Belfast Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The Research Portal is Queen's institutional repository that provides access to Queen's research output. Every effort has been made to ensure that content in the Research Portal does not infringe any person's rights, or applicable UK laws. If you discover content in the Research Portal that you believe breaches copyright or violates any law, please contact openaccess@qub.ac.uk.

Open Access
This research has been made openly available by Queen's academics and its Open Research team. We would love to hear how access to this research benefits you. – Share your feedback with us: http://go.qub.ac.uk/oa-feedback

Download date:10. Aug. 2024

Check for updates

Received: 8 February 2022 | Revised: 24 November 2022 | Accepted: 18 December 2022

DOI: 10.1002/hec.4648

RESEARCH ARTICLE

Health Economics WILEY

From financial wealth shocks to ill-health: Allostatic load and overload

Declan French

Queen's Management School, Belfast, UK

Correspondence
Declan French, Queen's Management School, Riddel Hall, 185 Stranmillis Road, Belfast, BT9 5EE UK.
Email: declan.french@qub.ac.uk

Abstract

A number of studies have associated financial wealth changes with health-related outcomes arguing that the effect is due to psychological distress and is immediate. In this paper, I examine this relationship for cumulative shocks to the financial wealth of American retirees using the allostatic load model of pathways from stress to poor health. Wealth shocks are identified from Health and Retirement Study reports of stock ownership along with significant negative discontinuities in high-frequency S&P500 index data. I find that a one standard deviation increase in cumulative shocks over two years increases the probability of elevated blood pressure by 9.5%, increases waist circumference by 1.2% and the cholesterol ratio by 6.1% for those whose wealth is all in shares. My findings suggest that the combined effect of random shocks to financial wealth over time is salient for health outcomes. This is consistent with the allostatic load model in which repeated activation of stress responses leads to cumulative wear and tear on the body.

KEYWORDS
allostatic load, elderly, health, stock market falls, stock ownership, wealth shock

1 | INTRODUCTION

Elderly Americans own over quarter of all U.S. wealth and over half have money invested in the stock market. A number of studies have associated stock market movements with hospital admissions and fatal car accidents arguing that the effect is due to psychological distress and is immediate. In this paper, I examine this relationship for American retirees using the allostatic load model of pathways from stress to poor health to show how stock market participation can cause ill health over the longer-term.

The body triggers a number of physiological responses to deal with stress including the production of stress hormones and anti-inflammatory proteins. Prolonged or repeated activation of stress responses can lead to strain on the body or *allostatic load* with disruption of metabolic, cardiovascular and immune systems. Biomarkers for dysregulation can then provide an early signal of imminent disease onset. Since 2006, the Health and Retirement Study (HRS) has collected blood-based biomarker data as well as physical measures including blood pressure in a biennial survey representative of the U.S. population over age 50. I examine the response of these allostatic load measures to wealth shocks over the previous two years.

I identify wealth shocks from statistically significant falls in high-frequency S&P500 index data along with individual stock ownership as reported in HRS. Returns are presumed to evolve continuously over time as an Itô process combined with a jump process and a fall then is an exceptionally negative standardized return (Bormetti et al., 2015; Lee & Mykland, 2008). I find that

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2023 The Authors. Health Economics published by John Wiley & Sons Ltd.

falls accumulated over two years are associated with higher systolic and diastolic blood pressure (DBP) as well as with larger waist circumference and higher cholesterol ratios which are all independent risk factors for cardiovascular disease. This result is consistent with the allostatic load model of repeated stress causing secondary health outcomes. It is also noteworthy as other studies have indicated that stock market returns have mainly psychological effects and these effects are largely coincident with price changes (Engelberg & Parsons, 2016; Giulietti et al., 2020). Unlike these authors who rely on aggregate population data I can also identify those most exposed to stock market fluctuations by estimating the percentage of wealth invested directly in stocks and mutual funds or indirectly through IRA/Keogh accounts.

This study is closest to Schwandt (2018) who finds that financial wealth changes across HRS waves affect an index of seven reported doctor-diagnosed conditions but mainly hypertension.[1] In contrast, I find this variable has no explanatory power for my allostatic load measures. This reinforces my view that random shocks to financial wealth and not simply changes in wealth are salient for health outcomes.

More broadly, my work contributes to the literature on the wealth-health gradient. Seeman et al. (2018) found an association between systolic blood pressure and blood glucose levels and the timing of the 2008–2010 Great Recession. Studies have demonstrated large effects on physical or mental health of house price increases (Fichera & Gathergood, 2016); extension of eligibility for state pension (Case, 2004) and lottery winnings (Lindahl, 2005; Lindqvist et al., 2020). However, other studies report weak or no evidence (e.g., Carman, 2013; Cesarini et al., 2016; Michaud & Van Soest, 2008; Östling et al., 2020) and results appear to depend on factors such as the subjectivity of the dependent health measure, chosen population sample, wealth measurement error or social security context. Recently, Erixson (2017) concluded that we still know little about *if* and *how* wealth affects health. This paper is therefore a contribution to our understanding of *how* wealth affects health.

My sample of elders is of special interest as older bodies are slower to recover from stress (Read & Grundy, 2012) and are more susceptible to overload due to a lifetime's exposure to stressors (Juster et al., 2010). Once retired their wealth and income is also particularly dependent on the vagaries of the stockmarket with 54% of those aged 65 and over owning shares and many reliant on defined contribution pension plans (Gomes et al., 2021; Jones, 2017). Although changes in finances are less associated with stress-induced health breakdown than divorce or death of a close relative they occur more frequently (Holmes & Rahe, 1967; Noone, 2017). The 2010 Stress in America survey reported that the two most commonly cited significant causes of stress for those aged over 65 are the economy (69%) and money (62%) (APA, 2010).

My finding that stock market falls increase allostatic load has a number of implications. First, older stock market investors should take account of potential welfare loss due to stress-related health conditions in managing their portfolio risk. Second, retirees should reduce their exposure to the stress of idiosyncratic price shocks by diversification or by making greater use of financial intermediaries and, third, there is a role for financial education in assisting the elderly to manage their portfolios with less stress.

2 | ALLOSTASIS AND ALLOSTATIC LOAD

The body reacts to a stressful event by turning on a physiological response and in normal circumstances turning this response off when the stress has passed. The purpose of this response is to maintain functioning of critical systems necessary for survival. But repeated activation of these reactions can lead to strain on the body potentially leading to disease (McEwen, 2017). This strain or *allostatic load* can take the form of elevated activity of bodily systems, changes in metabolism and wear and tear on organs and tissues (McEwen & Stellar, 1993) leading to lower physical function, frailty, reduced cognitive function and increased mortality risk among elders (Gruenewald et al., 2012; Juster et al., 2010).

The allostatic load model of the pathway from stress to poor health begins with changes in the *primary mediators* - stress hormones such as adrenaline, anti-inflammatory cytokines and in the longer-term glucocorticoids including cortisol (Figure 1).

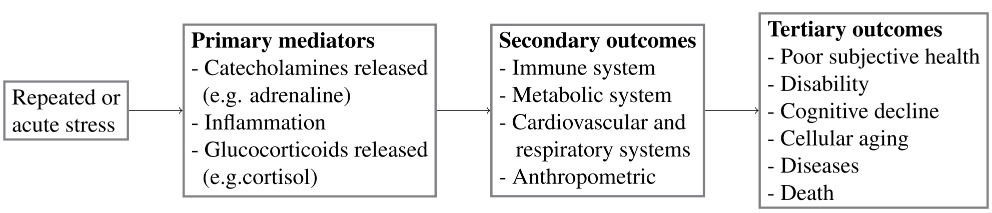

FIGURE 1 Allostatic load model. *Source*: Adapted from Read and Grundy (2012)

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Prolonged or repeated activation of stress responses can lead to sub-clinical *secondary outcomes* which include changes in cardiovascular, metabolic and immune systems (Read & Grundy, 2014). Conventional biomarkers indicative of dysregulation are prolonged blood pressure elevation, high cholesterol or anthropometric measures of obesity. Disruption of these physiological systems then in turn increases the risk of diseases or disorders which are the *tertiary outcomes*. Stress has been implicated in the aetiology of a wide range of diseases but the strongest evidence finds an association with cardiovascular disease and diabetes as well as psychiatric morbidity (Cohen et al., 2019; Guidi et al., 2021).

As allostatic load reflects multisystem dysregulation a range of biomarkers are used in its measurement. There is no standard best combination of measures accepted in the literature and in practice markers often vary between studies (Read & Grundy, 2012). Primary mediator data is not available in the HRS waves I study[2] and, in any case, often requires multiple days of collection to provide robust associations (Dowd et al., 2009). My focus instead is on a number of secondary outcome biomarkers also used in other recent studies (Stephan et al., 2016; Tampubolon & Maharani, 2018).

The most common perspective on stress posits that stressful events are those that are harmful or threatening with the imminence, uncontrollability, intensity and duration of the threat magnifying its effect (Cohen et al., 2019). Stock market falls are arguably random, intermittent events that are uncontrollable and unpredictable and empirical studies indicate that stock market fluctuations cause stress. Giulietti et al. (2020) attribute their finding of a causative link between stock market returns and fatal car accidents to the psychological distress of a direct negative effect on financial wealth. Engelberg and Parsons (2016) find daily stock returns linked to hospital admissions for psychological conditions such as anxiety, panic disorder and major depression. However, the explanatory variable in these studies is daily variation in stock market performance, that is, both positive and negative changes of any magnitude and not especially stressful events. In contrast, I focus on series of negative financial market shocks using stochastic process theory to identity extreme events. Their cumulative magnitude over time becomes my explanatory variable of interest consistent with the allostatic load model of cumulative wear and tear.

3 | DATA AND METHODOLOGY

3.1 | Data

The HRS is a biennial longitudinal survey of approximately 20,000 people designed to be representative of the U.S. population over the age of 50 covering health, employment, income, assets and retirement. Beginning wave 8 (collected 2006), blood-based biomarkers from fingersticks and dried blood spots as well as physical measures including blood pressure and waist circumference were collected during an enhanced face-to-face interview from a randomly selected half of the sample while the second half were then selected in the following wave. The first half were selected again for biomarker analysis in waves 10 and 12 while the second half were selected again in waves 11 and 13.

My analysis focuses on retired households, that is, the respondent and spouse (if applicable) consider themselves retired or are both not working for pay and not unemployed. The 3% of respondents whose interview was not fully completed on a specific day were excluded from the analysis. HRS imputes income and wealth variables where missing and the documentation notes that the imputation algorithms sometimes produce large anomalous amounts (Bugliari et al., 2020). For this reason, I winsorize total household income; total household assets; net value of stocks, mutual funds and investment trusts and the net value of IRA, Keogh accounts at the 99th percentile.

3.2 | Allostatic load measures

Allostatic load is the cumulative adaption of biological systems to stress over time (McEwen, 1998). Measures of long-term stress response are typically calculated from changes in three systems: cardiovascular, metabolic and immune (Read & Grundy, 2012).[3] In the HRS, the cardiovascular functioning indicators are:

- systolic blood pressure (SBP) – pressure against artery walls when the heart beats
- diastolic blood pressure (DBP) – pressure against artery walls between heart beats

the metabolic biomarkers are

- total cholesterol (TC) – often designated as a fat. Positively associated with the onset of cardiovascular disease and predictive of heart attack, stroke, kidney disease, artery disease and many other related conditions.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

- high density lipoprotein cholesterol (HDL) – “good cholesterol”. Higher blood levels associated with lower incidence of conditions affecting blood vessels.
- waist circumference – measurement with a tape taken at navel level. Waist circumference is preferred to BMI in the HRS as a predictor for cardiovascular risk and other adiposity-related conditions.
- glycosylated hemoglobin (HbA1C) – a measure of blood glucose (sugar). High levels are associated with diabetes, diabetes-related conditions such as cardiovascular disease and other factors such as altered diets, other diseases, drugs and toxins.
- cystatin C (CysC) – high levels are a marker of kidney disease.

and the immune system biomarker is

- C-reactive protein (CRP) – an indicator of inflammation. Elevation is associated with a range of acute and chronic conditions including infections, inflammatory diseases, injury, and malignancy.

See Crimmins et al. (2013) for more details. To maintain comparability of results across the different labs used to assay the dried blood spot samples, HRS recommends using the measurement values they adjust to match the distribution of results in a similarly aged nationally representative sample. After adjustment most biomarkers are approximately normally distributed albeit with a slight right skew. CRP follows a pronounced lognormal distribution.

TC is associated with cardiovascular disease while HDL is the “good cholesterol” associated with lower incidence of vascular conditions. I therefore follow Juster et al. (2010) and Tampubolon and Maharani (2018) in expressing these measures as a single ratio (TC/HDL).

3.3 | Stock market falls

Stock index dynamics are explored following the approach in Bormetti et al. (2015) building on techniques developed in Lee and Mykland (2008). Falls are identified at any point in time τ by testing whether the ratio of the realized return (r_τ) to local volatility (σ_τ) is below a given threshold (θ):

$$\frac{r_\tau}{\sigma_\tau} < \theta \tag{1}$$

There are a number of complications in estimating this statistic. The returns must first be purged of intraday volatility. As in Taylor and Xu (1997), I divide my raw return $r'_{t,m}$ on day t at time m by a correction factor ζ_m to give r_τ in Equation (1) where

$$r_\tau = \frac{r'_{t,m}}{\zeta_m} \text{ and } \zeta_m^2 = \frac{M \sum_{t=1}^{T} r'^2_{t,m}}{\sum_{t=1}^{T} \sum_{m=1}^{M} r'^2_{t,m}}$$

that is, ζ_m is the standard deviation of raw returns at time m divided by the standard deviation of all raw returns.

The second difficulty is in estimating local volatility in the presence of falls. Bormetti et al. (2015) use two alternatives - the realized absolute variation and the realized bipower variation – both in exponentially weighted moving average form:

$$\hat{\sigma}_\tau^{\text{abs}} = \frac{\alpha}{c} \sum_{j=1} (1-\alpha)^{j-1} |r_{\tau-j}| \text{ and } \hat{\sigma}_\tau^{\text{bv}} = \sqrt{\frac{\alpha}{c^2} \sum_{j=1} (1-\alpha)^{j-1} |r_{\tau-j}||r_{\tau-j-1}|} \tag{2}$$

where $c = \sqrt{\frac{2}{\pi}}$ is due to the asymptotic theory while the EWMA weighting is $\alpha = \frac{2}{N+1}$ for $N = 60$. With this choice of N, roughly 86% of the total weight in the EWMA calculation is due to the previous 60 data points. Only the previous returns at a time point where no fall was detected are included in the calculation of Equation (2) to ensure estimates are free of bias due to observed falls.

The test statistic in Equation (1) is now calculated. The threshold is taken as $\theta = -4$ as in Bormetti et al. (2015). As I have two estimators for local volatility from Equation (2), I follow these authors in choosing the intersection between the two sets of detected falls.

My stock market index is the Standard and Poor's stock market index of 500 large publicly-traded US companies (S&P500) provided by Tick Data. Lee and Mykland (2008) found that only 2% of shocks were detected using daily returns while higher

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

frequency observations made their statistical test more precise. I follow these authors in using 15-min returns which they found identified shocks coincident with the arrival of major news such as Federal Open Market Committee meetings or macroeconomic reports.

3.4 | Identification strategy

For each point in time τ on each interview date, the cumulative sum of all stock market falls over the previous two years is determined[4]:

$$F_\tau = \sum_{j=1}^{504\times 25} |r_{\tau-j}| \times \mathbb{1}\left(\frac{r_{\tau-j}}{\sigma} < \theta\right) \tag{3}$$

The average of F_τ for the interview date is then determined. The indicator variable takes the value of 1 for large stock market falls that is when the ratio of the realized return to local volatility $\frac{r_{\tau-j}}{\sigma}$ is below the threshold of $\theta = -4$ and takes the value of 0 otherwise. F_τ is then the cumulative sum of a number of these falls where each fall is expressed as a percentage. I focus on the cumulative size of falls as opposed to a simple count as the extent of physiological response depends on both the number and magnitude of stressful events (Clark et al., 2007). The time span considered in research using major stressful life event checklists is usually a reference period of one-year (Cohen et al., 2019) though this is perhaps motivated by known issues with recall over longer time spans in retrospective interviews (Shields & Slavich, 2017). I use a span of two years which is the gap between successive HRS waves.

Dramatic stock market falls may well reflect wider economic and political shocks which affect all individuals. To isolate the shock to financial wealth, I interact my cumulative stock market falls variable with a variable reflecting the respondent's exposure to stock price fluctuations. Following Schwandt (2018), this variable takes the form of the respondent's ratio of stock holdings to wealth $\left(\frac{S_{it}}{W_{it}}\right)$. The respondent's stock holdings (S_{it}) are the net value of stocks, mutual funds and investment trusts plus the share of retiree pension plans (i.e., IRA/Keogh accounts) invested in stocks or mutual funds.[5] Lifetime wealth (W_{it}) is calculated as the sum of current net household wealth plus discounted future household income.[6] As financial portfolios may be adjusted in response to stock market fluctuations, all of these variables are taken from the previous wave. Selected descriptive statistics are given in Table 1. The mean number of stock market falls in the two years before interview was 39.9; the mean cumulative stock market falls was 25.4% and mean stock holdings to wealth ratio was 6%. To give a sense of the financial significance of these falls, each fall equates to \$1625 on average for those with stock holdings or \$63,935 cumulatively over two years falls. Potential losses vary substantially with each fall representing only \$47 at the 10th percentile compared to \$4864 at the 90th percentile.

The basic model is then regression with fixed effects at individual level and clustered standard errors at household level:

$$y_{it} = \beta \frac{S_{i,t-1}}{W_{i,t-1}} F_t + \boldsymbol{\delta}' \mathbf{X}_{it} + \boldsymbol{\Theta} + \nu_i + \varepsilon_{it} \tag{4}$$

where for individual i interviewed on day t: y_{it} is the biomarker level; S_{it} stock holding; W_{it} lifetime wealth; $\mathbf{X}_{it}$ a vector of controls; $\boldsymbol{\Theta}$ is a vector of interview year, month and day of week dummies and ν_i are individual effects. Controls include age; region; marital status; the previous fraction of wealth in stocks $\left(\frac{S_{i,t-1}}{W_{i,t-1}}\right)$; the sum of all S&P500 falls (F_t); the S&P500 return over the past 2 years; average S&P500 level over the past 2 years. The previous fraction of wealth in stocks was also interacted with the three S&P500 variables. My parameter of interest β is the effect of stock market falls on biomarker levels for those respondents with stock holdings.

If the allostatic load model is useful in understanding the health response to financial market fluctuations then I should additionally find no effect of positive shocks to financial wealth on my biomarkers. Replacing Equation (1) by

$$\frac{r_\tau}{\sigma_\tau} > \theta \quad \text{where} \quad \theta = 4 \tag{5}$$

we can calculate the cumulative sum of all positive shocks to the S&P500 in the previous two years using the same methodology as in Equation (3) for falls. This variable is added to the baseline specification.

With this model, I am testing whether biomarker levels are high when stress related to financial wealth is high meaning either (i) high exposure to financial markets (ii) low level of financial markets (iii) low returns on financial assets (iv) high

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 Selected descriptive statistics - mean (s.d.)

	All		With stock holdings		No stock holdings	
Allostatic load						
Systolic blood pressure (mm Hg)	132.2	(20.9)	131.5	(19.81)	132.7	(21.54)
Diastolic blood pressure (mm Hg)	77.4	(11.8)	76.9	(11.3)	77.64	(12.1)
Cholesterol ratio (TC/HDL)	3.79	(1.15)	3.69	(1.11)	3.86	(1.18)
Waist circumference (in)	40.0	(6.28)	39.2	(5.86)	40.5	(6.47)
Glycosylated hemoglobin (%)	5.96	(1.00)	5.80	(0.77)	6.06	(1.10)
Cystatin C (mg/L)	1.26	(0.58)	1.20	(0.51)	1.29	(0.62)
C-reactive protein (μg/ml)	4.47	(9.33)	3.65	(8.35)	4.96	(9.83)
S&P 500 falls in past 2 years (%)	25.41	(8.60)	25.32	(8.67)	25.46	(8.56)
S&P 500 rises in past 2 years (%)	17.90	(3.73)	17.68	(3.73)	18.03	(3.72)
S&P 500 return over past 2 years (%)	14.81	(15.40)	14.53	(15.53)	14.98	(15.32)
S&P 500 level	1525.5	(356.9)	1495.7	(343.5)	1543.0	(363.5)
Stock holdings to wealth ratio	0.06	(0.11)	0.16	(0.14)	0	0
Age	74.24	(9.07)	75.36	(8.16)	73.58	(9.51)
Female	0.63	(0.48)	0.58	(0.49)	0.65	(0.48)
Race						
White	0.80	(0.40)	0.94	(0.24)	0.71	(0.45)
Black	0.16	(0.36)	0.04	(0.20)	0.22	(0.42)
Marital status						
Married	0.49	(0.50)	0.64	(0.48)	0.40	(0.49)
Divorced	0.11	(0.31)	0.06	(0.23)	0.14	(0.35)
Widowed	0.30	(0.46)	0.24	(0.43)	0.34	(0.47)
Region						
Northeast	0.15	(0.36)	0.16	(0.37)	0.15	(0.36)
Midwest	0.24	(0.43)	0.30	(0.46)	0.21	(0.41)
South	0.42	(0.49)	0.34	(0.47)	0.47	(0.50)
West	0.18	(0.39)	0.20	(0.40)	0.17	(0.38)
Year of interview (%)						
2006	17.50	(37.96)	18.93	(39.18)	16.59	(37.20)
2007	0.05	(2.26)	0.04	(2.03)	0.06	(2.38)
2008	16.99	(37.57)	17.54	(38.04)	16.69	(37.29)
2009	0.01	(3.50)	0.08	(2.87)	1.46	(3.82)
2010	13.01	(33.65)	14.78	(35.49)	11.97	(32.46)
2011	2.32	(15.06)	2.39	(15.28)	2.28	(14.28)
2012	16.60	(37.21)	16.25	(36.90)	16.81	(37.39)
2013	5.05	(7.09)	3.30	(5.74)	6.09	(7.78)
2014	17.85	(38.29)	16.70	(37.54)	18.37	(38.73)
2015	0.08	(2.86)	0.03	(1.66)	0.11	(3.37)
2016	13.62	(0.34)	11.65	(32.08)	14.79	(35.50)
Number of individuals	12427		4477		7950	
Number of observations	19609		7274		12335	

Note: Sample is retired households where the respondent and spouse considered themselves retired or were both not working for pay and not unemployed in previous wave. Biomarker measures are not available for full sample due to lack of consent.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

number of financial wealth shocks or (v) large financial wealth shocks. My hypothesis is that only (iv) and (v) capture stress related to financial wealth.

4 | RESULTS

4.1 | Main results

The results of estimating the model in Equation (4) for each of the seven allostatic load measures are presented in Table 2 for selected variables with full results in Table B1 of the online supplementary. There is a clear statistically significant effect of cumulative stock market falls over the past two years on blood pressure, cholesterol and waist measurement for those actually owning shares (first row). The coefficients of $\hat{\beta} = 0.466$ and $\hat{\beta} = 0.229$ indicate that a one standard deviation change in cumulative falls in the S&P500 changes SBP by 4.0 mm Hg (3.0% of mean values) and DBP by 2.0 mm Hg (2.5% of the mean) for those whose wealth is all in shares.[7] These effects are substantial as, by way of comparison, taking antihypertensive medications for a year decreases SBP by only 13.7 mm Hg (Tobe et al., 2007). The estimated coefficient of $\hat{\beta} = 0.027$ in the cholesterol model means that a one SD change in stock market falls changes the cholesterol ratio by 0.232 or 6.1% of mean values for those whose wealth is all in shares although the effect is only statistically significant at the lower 10% level. The $\hat{\beta} = 0.058$ for the other metabolic system biomarker equates to a one SD change in stock market falls changing waist circumference by 0.499 in or 1.2% of mean values for those whose wealth is all in shares.[8] Coefficient estimates for the other stress response measures are statistically insignificant. The stress-HbA1C relationship can be confounded by race, ethnicity; individual physiological, psychological, and health behaviour processes; family and peer relationships; and other environmental and contextual factors as well as interindividual biological and genetic differences (Hilliard et al., 2016). Measures of kidney/liver function such as CysC were not included in the original conceptualization of allostatic load and are still uncommon with creatinine typically the preferred biomarker when included.[9]

Estimated coefficients for the effect of positive shocks on those with stock holdings are also given and it is clearly seen that there is no association between positive shocks to financial wealth and stress responses. This result contrasts with the conclusion in Schwandt (2018) that financial wealth increases have strongly positive effects on the onset of doctor-diagnosed high blood pressure. However, positive shocks are seen to lower the cholesterol ratio and glycosylated hemoglobin (HbA1C) for all respondents regardless of stock ownership (Table B1). Stock market performance may therefore be proxying for some wider socioeconomic health determinant but as the relationship is unclear we should be wary of studies which find associations between aggregate health outcomes and stock market fluctuations without data on individual stock ownership.

The effect sizes I report are larger than relationships described as “strong”in Engelberg and Parsons (2016) (one SD decline in stock returns increases daily hospital admissions by 0.18%) or “important” in Giulietti et al. (2020) (one SD decline in stock returns increases fatal car accidents by 0.6%). Unlike in my data, micro-level data on share ownership was not available to these authors in their studies and the strength of any relationship will be inevitably attenuated. Also unlike their work, my focus has been on extreme negative events which both sets of authors acknowledged in sensitivity analyses were driving their key results.

TABLE 2 Main results

	Cardiovascular		Metabolic				Immune
	SBP	DBP	TC/HDL	Waist	HbA1c	CysC	CRP
S&P500 falls × (stock/wealth)	0.466**	0.229**	0.027*	0.058**	−0.001	−0.002	0.155
	(0.184)	(0.103)	(0.015)	(0.027)	(0.007)	(0.004)	(0.105)
S&P500 rises × (stock/wealth)	−0.571	−0.447	−0.000	−0.120	0.010	0.018	0.101
	(0.650)	(0.358)	(0.048)	(0.102)	(0.027)	(0.014)	(0.320)
Within R^2	0.023	0.059	0.056	0.011	0.056	0.172	0.012
Number of individuals	11476	11476	10159	11317	10645	10592	10637
Number of observations	19769	19769	16581	19514	17813	17650	17820

Note: Coefficient estimates for model in Equation (4). Dependent variables are systolic blood pressure (SBP), diastolic blood pressure (DBP), cholesterol ratio (TC/HDL), waist circumference (Waist), glycosylated haemoglobin (HbA1c), Cystatin C (CysC) and C-reactive protein (CRP). The ratio of stock holdings to financial wealth (*stock/wealth*) is taken from the previous wave. Other controls not displayed: stock/wealth, S&P500 falls, S&P500 rises, S&P500 level × (stock/wealth), S&P500 return × (stock/wealth), dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Full results in Table B1. Standard errors in parentheses are clustered by household.

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

An alternative analysis of the blood pressure measures is presented in Table A1 of the Appendix where I use dichotomous indicators of high blood pressure. I find that a one SD change in cumulative falls in the S&P500 reduces the probability of having normal blood pressure by 7.7% and increases the probability of having elevated blood pressure (SBP >120 mm Hg) by 9.5% for those whose wealth is all in shares.[10]

4.2 | Robustness checks

I undertake a series of checks which confirm the robustness of my findings. In Table 3, coefficient estimates are given for the fixed effects model augmented by sets of additional controls. The baseline results from Table 2 are given in the first row for reference. First, additional household finance variables including wealth, income, debt and health insurance are added to the baseline specification. Second, measures of the state of the economy over the past two years are added to the baseline specification as the effect of my stock market falls variable on health may reflect macroeconomic developments and not changes in individual financial wealth. Third, forward-looking uncertainty measures at the time of the interview are added to the baseline specification for economic policy uncertainty (Baker et al., 2016) and geopolitical risk (Caldara & Iacoviello, 2018) to account for anticipated events which may be correlated with stock market fluctuations and stressful for respondents. Estimates are largely unchanged.

Stock holdings were defined in Section 3.4 as the sum of stocks, mutual funds and investment trusts plus the share of pensions invested in stocks or mutual funds. Using the 2016 Survey of Consumer Finances, Bhutta et al. (2020) indicate that the percent of US families owning stocks was 13.9% with conditional median $26,600; pooled investment funds 10.0% (median $121,200) and retirement accounts 52.1% (median $63,800). It therefore seems reasonable to use an overall market index to reflect fluctuations in financial market wealth. According to S&P Global, the S&P 500 Index represents approximately 80% of total U.S. stock market value and is a good reflection of overall market movement. The S&P MidCap 400 measures the performance of 400 mid-sized companies representing only 6% of the U.S. equities market. We would therefore not expect the biomarkers of those with financial wealth in our sample to be much affected by this index. This is reflected in coefficient estimates in Table 4 where the effect of unexpected falls in this index on biomarkers is statistically insignificant.

The next set of checks (Table 5) demonstrates that results are consistent with the allostatic load conceptual model. The physiological response to stress accumulates gradually over time and hence past falls should always contribute to a significant allostatic load. To validate this, the cumulative falls variable F_t in Equation (4) is divided into two new variables: *recent* falls in the previous quarter/month/week/day and all *past* falls over past two years excluding these recent falls. These two new variables

TABLE 3 Results with additional controls - coefficient estimates for stock market falls interacted with $\frac{\text{stock}}{\text{wealth}}$

	SBP	DBP	TC/HDL	Waist
Baseline	0.466**	0.229**	0.027*	0.058**
	(0.184)	(0.103)	(0.015)	(0.027)
+ Household finances	0.432**	0.210**	0.028*	0.059**
	(0.186)	(0.103)	(0.015)	(0.028)
+ State of economy	0.472**	0.229**	0.030**	0.061**
	(0.185)	(0.103)	(0.015)	(0.028)
+ Economic uncertainty	0.457**	0.225**	0.026*	0.058**
	(0.185)	(0.103)	(0.015)	(0.027)

Note: Coefficient estimates for S&P500 falls × (stock/wealth) for model in Equation (4). Additional controls are: *Household finances* is (log) net household wealth, (log) household income, (log) household debt and dummies for each of government, private or other health insurance; *State of economy* is average of monthly values (unless otherwise) over past year of Real GDP per capita (quarterly), Unemployment rate, Industrial production index, Industrial production growth rate, Manufacturing capacity utilization, Personal consumption expenditures, Personal consumption growth, Consumer Price Index, New one family homes sold, New one family homes growth, Total construction spend, Total construction growth, Manufacturer's new orders, Manufacturer's orders growth, Retail sales, Retail sales growth; *Economic uncertainty* is economic policy uncertainty index (Baker et al., 2016) and geopolitical risk (Caldara and Iacoviello, 2018) at interview date. Other controls not displayed: S&P500 level × (stock/wealth); S&P500 return × (stock/wealth), S&P500 falls, S&P500 level, S&P500 return, Stock/wealth ratio, dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Standard errors in parentheses are clustered by household.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 Falls in S&P MidCap 400

	SBP	DBP	TC/HDL	Waist
Baseline	0.466**	0.229**	0.027*	0.058**
	(0.184)	(0.103)	(0.015)	(0.027)
S&P MidCap 400 falls × (stock/wealth)	−0.268	−0.334	0.032	0.014
	(0.462)	(0.269)	(0.034)	(0.072)

Note: Coefficient estimates for S&P MidCap 400 falls × (stock/wealth) for model in Equation (4). *Baseline* are estimates for S&P500 falls × (stock/wealth) from Table 2. Other controls: S&P MidCap 400 return × (stock/wealth), S&P MidCap 400 rises, S&P MidCap 400 level, S&P MidCap 400 return, stock/wealth ratio, dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Standard errors in parentheses are clustered by household.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 5 Dynamic effcts - coefficient estimates for stock market falls interacted with ratio of stock to wealth

	SBP		DBP		TC/HDL		Waist	
	Past	Recent	Past	Recent	Past	Recent	Past	Recent
Baseline	0.466**	-	0.229**	-	0.027*	-	0.058**	
	(0.184)	-	(0.103)	-	(0.015)	-	(0.027)	
Quarter	0.472**	0.341	0.270**	−0.039	0.045**	−0.035	0.086**	−0.085
	(0.239)	(0.592)	(0.127)	(0.336)	(0.019)	(0.045)	(0.039)	(0.113)
Month	0.517***	−0.038	0.250**	−0.303	0.025	0.037	0.062**	0.007
	(0.196)	(0.739)	(0.109)	(0.419)	(0.016)	(0.049)	(0.030)	(0.123)
Week	0.518***	11.714***	0.246**	7.468***	0.027*	0.038	0.059**	−0.209
	(0.188)	(4.192)	(0.105)	(2.441)	(0.015)	(0.350)	(0.027)	(0.886)
Day	0.482**	16.692**	0.212*	11.462***	0.030*	−0.609	0.073**	−0.935
	(0.195)	(8.175)	(0.109)	(4.364)	(0.016)	(0.620)	(0.029)	(1.480)

Note: Coefficient estimates for S&P500 falls × (stock/wealth) for model in (4). *Baseline* is estimates for falls over past 2 years. In the next sets of estimates, *Recent* are falls over recent quarter/month/week/day. *Past* are falls over past 2 years excluding recent quarter/month/week/day. Other controls not displayed: stock/wealth, S&P500 falls, S&P500 rises, S&P500 rises × (stock/wealth), S&P500 level × (stock/wealth), S&P500 return × (stock/wealth), dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Standard errors in parentheses are clustered by household.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

are then also interacted with the fraction of wealth in stocks. Past falls are almost always statistically significant for each of the allostatic load measures regardless of the time period considered. More recent falls never matter for the cholesterol ratio or waist circumference but interestingly coefficient estimates for falls within the last week or previous day are very large and significant for both blood pressure measurements.

Instrumental variables regressions are also included in the online supplementary appendix using instruments for current fraction of wealth in stocks and interaction terms but with the sample of retired households based on the previous wave (Table B2). The coefficient estimates are larger than the baseline estimates above as are the standard errors.

The specification in Schwandt (2018) gives the estimates in Table B4. The main variable of interest in this model (the interaction of S&P500 return and stock ownership) is statistically insignificant in all regressions with allostatic load biomarkers or self-reported doctor-diagnosed health conditions as dependent variable. This result provides support to my focus on stock market falls in explaining allostatic load changes.

4.3 | Non-response, attrition and effect heterogeneity

Longitudinal studies of ageing are subject to attrition due to health, cognition problems and mortality. The HRS tries to minimize non-response and attrition by paying for participation; by using proxy respondents to answer on participants' behalf; by maintaining contact through regular communication and by seeking interviews even after multiple missed waves (Fisher & Ryan, 2018). As a result, selection effects due to non-response are substantially reduced in HRS panel data analyses of wealth, health and labour participation (Michaud et al., 2011).

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 Fixed-effects regression with sample selection - coefficient estimates for stock market falls interacted with $\frac{\text{stock}}{\text{wealth}}$

	SBP	DBP	TC/HDL	Waist
Baseline	0.466**	0.229**	0.027*	0.058**
	(0.184)	(0.103)	(0.015)	(0.027)
With sample selection	0.508***	0.268***	0.039***	0.029
	(0.163)	(0.096)	(0.015)	(0.035)

Note: Coefficient estimates for model in (6). Other controls in main model as in Table 2. Controls in selection model: gender, age, (log) number of hospital visits in previous 2 years, number of doctor diagnosed health problems, number of difficulties with Activities of Daily Living and dummies for race (1), Hispanic, region (3), marital status (4), government health insurance, doctor diagnosed diabetes, physical activity frequency - vigorous (1) moderate (1) light (1). Bootstrapped standard errors in parentheses are clustered by person.

$*p < 0.10, **p < 0.05, ***p < 0.01$.

Lower participation rates in many surveys with biomeasures are observed due to the intrusiveness of physical measurements and blood-based biological samples. The propensity to consent has been found to vary significantly by respondent characteristics. A secondary data analysis of the 2006 HRS found lower consent among those with functional limitations (Sakshaug et al., 2010) while a survey drawn from a national mobile panel found a higher willingness to participate among those who had attended a doctor or been hospitalised in the previous year (Boyle et al., 2021). The HRS blood spot completion rate varied from 81% in 2006% to 86% in 2016 while consent is generally higher for the physical measures.

To account for potential biases due to biomeasure non-consent, I augment the model in Equation (4) with a binary selection process s_{it} for those providing measures out of all those eligible for the enhanced interview:

$$\begin{aligned} y_{it} &= \beta \frac{S_{i,t}}{W_{i,t}} F_t + \boldsymbol{\delta}' \mathbf{X}_{it} + \boldsymbol{\Theta} + \nu_{1i} + \varepsilon_{1it} \\ s_{it} &= \mathbb{1}\left(\boldsymbol{\alpha}' \mathbf{Z}_{it} + \nu_{2i} + \varepsilon_{2it} > 0\right) \end{aligned} \tag{6}$$

where $\mathbf{Z}_{it}$ is a vector of covariates modelling selection.[11] Individual effects ν_1 and ν_2 are allowed correlate. Errors ε_1 and ε_2 are also allowed correlate and are independent of the individual effects. Results are given in Table 6 and are similar to previous estimates.

Effect heterogeneity by gender, age, lifetime wealth, education level and stock market expectations is explored in Table B3 of the online supplementary appendix. The interaction terms are generally statistically insignificant except for waist circumference. Those with college education experience effectively no effect of falls overall (others experience significant effect) while those with high expectations of stock market growth experience all of the effect (others experience no effect).

A causal interpretation of estimates from [4] requires that treatment assignment (stock market falls) is independent of the outcome (biomarker level) conditional on known and observed covariates. Stock market falls are exogenous but those individuals with a higher fraction of wealth in stocks before the falls occur will receive a greater amount of "treatment". Stock holdings in the previous wave could plausibly vary in ways connected with eventual health outcomes through omitted variables. The identification strategy deals with some but not all conceivable confounders.

The relationship between stress and systemic physiological dysregulations is not straightforward and not linear. Activation of responsive physiological systems above the threshold of successful adaption leads to allostatic load. Also the systems involved in responding to stress operate dynamically, nonlinearly and interactively (Juster et al., 2010). There is therefore no simple econometric model as yet to adequately reflect the complexity of the relationship between stress and biomarkers.

5 | DISCUSSION AND CONCLUSION

Previous studies have associated stock market movements with health-related outcomes arguing that the effect is due to psychological distress and is immediate. In this paper, I have shown how stock market participation among American retirees can cause ill health over the longer-term. The cumulative effect of extreme negative events as indicated by the allostatic load model better identifies longer-term health impacts on investors than simple changes in financial wealth. I find that a one standard deviation increase in cumulative falls over two years in a stock market index increases SBP by 4.0 mm Hg (3.0% of mean values); increases DBP by 2.0 mm Hg (2.5% of mean); reduces the probability of normal blood pressure by 7.7%; increases waist circumference by 0.499 in (1.2% of mean values) and increases the cholesterol ratio by 0.232 (6.1% of mean) for those whose

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

wealth is all in shares. These effects are substantial and are seen to be robust across specifications with additional controls, adjustments for endogeneity and selection bias. The identification strategy encourages a causal interpretation of these estimates. Higher systolic and DBP along with large waist circumference and higher cholesterol ratios are independent risk factors for cardiovascular problems (Flint et al., 2019). Among older people, elevated blood pressure is additionally related to kidney failure, retinal disease, cognitive decline, dementia and many other clinical conditions (Crimmins et al., 2008).

The novelty of this study is that I have shown how results are consistent with the allostatic load model for the aetiology of stress-related disease. There are a number of other strengths to my study. I am not reliant on measures of subjective general health status as in most previous studies. I see in my estimates that stock market fluctuations may proxy for wider socio-economic health determinants and that therefore I should be sceptical about results from aggregate studies. My study instead uses micro-level data on share ownership to establish a relationship. Lastly, I use the econometric literature on jump identification to isolate significant negative discontinuities in the evolution of stock market returns and demonstrate that these shocks are the only relevant explanatory variable.

The relevance of this result depends on the extent of retiree stock ownership and the typical fraction of household wealth in financial assets. The US has unusually high equity market participation rates of around 50% – partly driven by investment through retirement accounts – but only around 30% of household assets are financial investments (Badarinza et al., 2016). There is some evidence that the current environment of low interest rates has encouraged investor risk-taking (The Economist, 2020). Also, the advent of mobile retail brokerage applications will likely increase participation rates further just as reductions in information and transaction costs due to new technologies have increased household investment on the stock market in the past (Bogan, 2008).

There are a number of implications from these results. The welfare loss of stress-related health conditions in addition to potential psychological distress should be considered by older stock market investors. Although divestment from stocks in later life is standard financial theory, advisers often advise the opposite in practice (Mullainathan et al., 2012) and empirical evidence for the substitution of stocks for safer assets as people age is scarce (Guiso & Sodini, 2013). Retail investors tend to hold highly undiversified portfolios exposed to idiosyncratic price shocks and should be encouraged to diversify or invest in mutual funds or make greater use of financial intermediaries (Gomes et al., 2021). Analysis of the 2016 HRS survey shows that less than one-fifth of the sample receive financial help related to investment (Kim et al., 2019).

Portfolio managers would then perform the additional role of information stress managers mitigating the impact of bad news (Ameriks & Zeldes, 2004; Pagel, 2018). Investors in financial markets overreact to unexpected and dramatic news events (De Bondt & Thaler, 1985) with retail investors particularly prone to reactions divorced from economic fundamentals (Peress & Schmidt, 2021). This is a particular challenge for older investors. The elderly have reduced cognitive function (Humes & Floyd, 2005), worse judgement and decision-making (Sanfey & Hastie, 2000), lower financial literacy (Finke et al., 2017) and seek less financial information when making decisions (Kim & Kim, 2010). There is a role therefore for financial education in assisting the elderly to manage their portfolios with less stress.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available from Health and Retirement Study website at https://hrs.isr.umich.edu/data-products.

ORCID

Declan French https://orcid.org/0000-0001-9360-9429

ENDNOTES

[1] Schwandt (2018) refers to wealth changes over each biennial HRS wave as "wealth shocks". I prefer to reserve this term for significant negative discontinuities in the evolution of asset prices.

[2] A much broader range of blood-based biomarkers including typical stress-related primary mediators have become available through the HRS Venous Blood Study since the 2016 wave.

[3] Authors often use the individual biomarker values to calculate a composite measure of allostatic load in the form of an index. In their review article, Juster et al. (2010) find different biomarkers are associated with different pathological pathways and conclude that support for the analysis of an overall index is therefore mixed.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

[4] Returns at 15-min intervals during NYSE trading hours (930a.m. to 400p.m.) for the past 504 trading days in two years are tested.

[5] HRS does not contain detail about the share of equities in any 401(K) plans still held by retirees although Schwandt (2018) and Sabelhaus et al. (2008) indicate that these plans are usually cashed out or rolled over into IRAs upon retirement.

[6] That is, lifetime wealth, W_{it}, for individual i is: $W_{it} = \text{Wealth}_{it} + \sum_{x=0}^{X} \text{Income}_x \times \gamma^x \times P(\text{individual } i \text{ survives to year } x)$ where $\gamma = \frac{1}{1+3\%}$, X is year when aged 105 years and survival probabilities are given by U.S. Social Security Area life tables. Wealth_{it} is current net household wealth including housing wealth.

[7] For systolic blood pressure: $0.466 \times 8.60 = 4.0$ and this is $4.0/132.2 = 3.0\%$ of mean values. For DBP: $0.229 \times 8.60 = 2.0$ and this is $2.0/77.4 = 2.5\%$ of mean values.

[8] Estimates appear plausible. Johnston et al. (2009) found a 1% change in annual household income was associated with a $0.01 \times 0.974 = 0.010$ mm Hg reduction in SBP for English adults aged 26+. Davillas et al. (2019) found a 1% change in monthly gross household income was associated with a $0.01 \times 0.707 = 0.007$ mm Hg reduction in DBP and a $0.01 \times 0.138 = 0.001$ reduction in cholesterol ratio for British adults aged 16+.

[9] Schwandt (2018) finds that financial wealth changes across HRS waves affect an index of seven doctor-diagnosed conditions but mainly hypertension (Tables 3 and 4 of his paper). Results in Table A1 indicate that this is due to large stock market decreases between waves with stock market increases having no appreciable effect. One of his main results is that "a 10 percent wealth shock is associated with an improvement of 2–3 percent of a standard deviation in physical health". Conclusions do not reflect the analysis of effect asymmetry as the author considered these tests to have low power.

[10] For normal blood pressure: $0.009 \times 8.60 = 0.077$. For elevated blood pressure: $0.011 \times 8.60 = 0.095$.

[11] Sakshaug et al. (2010) found the propensity to consent was greater for patients with diabetes and Hispanic respondents matched with bilingual Hispanic interviewers while lower for younger respondents, those with functional limitations and those who infrequently participated in mildly vigorous activity. Boyle et al. (2021) found a correlation with gender, age, ethnicity, number of doctor visits, number of hospital visits and medical conditions.

REFERENCES

Ameriks, J., Zeldes, S. P., 2004. How do household portfolio shares vary with age. Technical Report. working paper, Columbia University.

APA. (2010). *Stress in America Findings full report*. American Psychological Association.

Badarinza, C., Campbell, J. Y., & Ramadorai, T. (2016). International comparative household finance. *Annual Review of Economics*, *8*(1), 111–144. https://doi.org/10.1146/annurev-economics-080315-015425

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Bhutta, N., Bricker, J., Chang, A. C., Dettling, L. J., Goodman, S., Hsu, J. W., Moore, K. B., Reber, S., Henriques Volz, A., & Windle, R. (2020). Changes in us family finances from 2016 to 2019: Evidence from the survey of consumer finances. *Federal Reserve Bulletin*, *106*(5), 1–42. https://doi.org/10.17016/bulletin.2020.106

Bogan, V. (2008). Stock market participation and the internet. *Journal of Financial and Quantitative Analysis*, *43*(1), 191–211. https://doi.org/10.1017/s0022109000002799

Bormetti, G., Calcagnile, L. M., Treccani, M., Corsi, F., Marmi, S., & Lillo, F. (2015). Modelling systemic price cojumps with Hawkes factor models. *Quantitative Finance*, *15*(7), 1137–1156. https://doi.org/10.1080/14697688.2014.996586

Boyle, J., Berman, L., Dayton, J., Iachan, R., Jans, M., & ZuWallack, R. (2021). Physical measures and biomarker collection in health surveys: Propensity to participate. *Research in Social and Administrative Pharmacy*, *17*(5), 921–929. https://doi.org/10.1016/j.sapharm.2020.07.025

Bugliari, D., Campbell, N., Chan, C., Hayden, O., Hayes, J., Hurd, M., Karabatakis, A., Main, R., Mallett, J., McCullough, C., Meijer, E., Moldoff, M., Pantoja, J., Rohwedder, S., & St. Clair, P. (2020). *RAND HRS longitudinal file 2016 (V2) documentation*. RAND Center for the Study of Aging.

Caldara, D., & Iacoviello, M. (2018). *Measuring geopolitical risk*. Federal Reserve Board International Finance Discussion Paper No.1222.

Carman, K. G. (2013). Inheritances, intergenerational transfers, and the accumulation of health. *The American Economic Review*, *103*(3), 451–455. https://doi.org/10.1257/aer.103.3.451

Case, A. (200). Does money protect health status? Evidence from South African pensions. In *Perspectives on the economics of aging* (pp. 287–312). University of Chicago Press.

Cesarini, D., Lindqvist, E., Östling, R., & Wallace, B. (2016). Wealth, health, and child development: Evidence from administrative data on Swedish lottery players. *Quarterly Journal of Economics*, *131*(2), 687–738. https://doi.org/10.1093/qje/qjw001

Clark, M. S., Bond, M. J., & Hecker, J. R. (2007). Environmental stress, psychological stress and allostatic load. *Psychology Health & Medicine*, *12*(1), 18–30. https://doi.org/10.1080/13548500500429338

Cohen, S., Murphy, M. L., & Prather, A. A. (2019). Ten surprising facts about stressful life events and disease risk. *Annual Review of Psychology*, *70*(1), 577–597. https://doi.org/10.1146/annurev-psych-010418-102857

Crimmins, E., Faul, J., Kim, J. K., Guyer, H., Langa, K., Ofstedal, M. B., Sonnega, A., Wallace, R., Weir, D., 2013. *Documentation of biomarkers in the 2006 and 2008 health and retirement study*. Technical Report. : Institute for Social Research, University of Michigan.

Crimmins, E., Guyer, H., Langa, K., Ofstedal, M. B., Wallace, R., Weir, D., 2008. *Documentation of physical measures, anthropometrics and blood pressure in the health and retirement study*. Technical Report. : Institute for Social Research, University of Michigan.

Davillas, A., Jones, A. M., & Benzeval, M. (2019). The income-health gradient: Evidence from self-reported health and biomarkers in understanding society. In *Panel data econometrics* (pp. 709–741). Elsevier.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

Dowd, J. B., Simanek, A. M., & Aiello, A. E. (2009). Socio-economic status, cortisol and allostatic load: A review of the literature. *International Journal of Epidemiology*, *38*(5), 1297–1309. https://doi.org/10.1093/ije/dyp277

Engelberg, J., & Parsons, C. A. (2016). Worrying about the stock market: Evidence from hospital admissions. *The Journal of Finance*, *71*(3), 1227–1250. https://doi.org/10.1111/jofi.12386

Erixson, O. (2017). Health responses to a wealth shock: Evidence from a Swedish tax reform. *Journal of Population Economics*, *30*(4), 1281–1336. https://doi.org/10.1007/s00148-017-0651-2

Fichera, E., & Gathergood, J. (2016). Do wealth shocks affect health? New evidence from the housing boom. *Health Economics*, *25*, 57–69. https://doi.org/10.1002/hec.3431

Finke, M. S., Howe, J. S., & Huston, S. J. (2017). Old age and the decline in financial literacy. *Management Science*, *63*(1), 213–230. https://doi.org/10.1287/mnsc.2015.2293

Fisher, G. G., & Ryan, L. H. (2018). Overview of the health and retirement study and introduction to the special issue. *Work, Aging and Retirement*, *4*, 1–9. https://doi.org/10.1093/workar/wax032

Flint, A. C., Conell, C., Ren, X., Banki, N. M., Chan, S. L., Rao, V. A., Melles, R. B., & Bhatt, D. L. (2019). Effect of systolic and diastolic blood pressure on cardiovascular outcomes. *New England Journal of Medicine*, *381*(3), 243–251. https://doi.org/10.1056/nejmoa1803180

Giulietti, C., Tonin, M., & Vlassopoulos, M. (2020). When the market drives you crazy: Stock market returns and fatal car accidents. *Journal of Health Economics*, *70*, 102245. https://doi.org/10.1016/j.jhealeco.2019.102245

Gomes, F., Haliassos, M., & Ramadorai, T. (2021). Household finance. *Journal of Economic Literature*, *59*(3), 919–1000. https://doi.org/10.1257/jel.20201461

Gruenewald, T. L., Karlamangla, A. S., Hu, P., Stein-Merkin, S., Crandall, C., Koretz, B., & Seeman, T. E. (2012). History of socioeconomic disadvantage and allostatic load in later life. *Social Science and Medicine*, *74*(1), 75–83. https://doi.org/10.1016/j.socscimed.2011.09.037

Guidi, J., Lucente, M., Sonino, N., & Fava, G. A. (2021). Allostatic load and its impact on health: A systematic review. *Psychotherapy and Psychosomatics*, *90*(1), 11–27. https://doi.org/10.1159/000510696

Guiso, L., & Sodini, P. (2013). *Household finance: An emerging field, handbook of the economics of finance*. Elsevier.

Hilliard, M. E., Yi-Frazier, J. P., Hessler, D., Butler, A. M., Anderson, B. J., & Jaser, S. (2016). Stress and a1c among people with diabetes across the lifespan. *Current Diabetes Reports*, *16*(8), 1–10. https://doi.org/10.1007/s11892-016-0761-3

Holmes, T. H., & Rahe, R. H. (1967). The social readjustment rating scale. *Journal of Psychosomatic Research*, *11*(2), 213–218. https://doi.org/10.1016/0022-3999(67)90010-4

Humes, L. E., & Floyd, S. S. (2005). Measures of working memory, sequence learning, and speech recognition in the elderly. *Journal of Speech, Language, and Hearing Research*, *48*(1), 224–235. https://doi.org/10.1044/1092-4388(2005/016)

Johnston, D. W., Propper, C., & Shields, M. A. (2009). Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient. *Journal of Health Economics*, *28*(3), 540–552. https://doi.org/10.1016/j.jhealeco.2009.02.010

Jones, J. M. (2017). U.S. Stock ownership down among all but older, higher-income. Retrieved from https://news.gallup.com/poll/211052/stock-ownership-down-among-older-higher-income.aspx. Accessed 07 10 2021.

Juster, R. P., McEwen, B. S., & Lupien, S. J. (2010). Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neuroscience and Biobehavioral Reviews*, *35*(1), 2–16. https://doi.org/10.1016/j.neubiorev.2009.10.002

Kim, H., & Kim, J. (2010). Information search for retirement plans among financially distressed consumers. *Journal of Family and Economic Issues*, *31*(1), 51–62. https://doi.org/10.1007/s10834-009-9179-2

Kim, H. H., Maurer, R., & Mitchell, O. S. (2019). *How cognitive ability and financial literacy shape the demand for financial advice at older ages*. Working Paper 25750. National Bureau of Economic Research.

Lee, S. S., & Mykland, P. A. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies*, *21*(6), 2535–2563. https://doi.org/10.1093/rfs/hhm056

Lindahl, M. (2005). Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income. *Journal of Human Resources*, *40*(1), 144–168. https://doi.org/10.3368/jhr.xl.1.144

Lindqvist, E., Östling, R., & Cesarini, D. (2020). Long-run effects of lottery wealth on psychological well-being. *The Review of Economic Studies*, *87*(6), 2703–2726. https://doi.org/10.1093/restud/rdaa006

McEwen, B. (2017). Stress: Homeostasis, rheostasis, reactive scope, allostasis and allostatic load. In *Reference module in neuroscience and biobehavioral psychology*. Elsevier.

McEwen, B. S. (1998). Stress, adaptation, and disease: Allostasis and allostatic load. *Annals of the New York Academy of Sciences*, *840*(1), 33–44. https://doi.org/10.1111/j.1749-6632.1998.tb09546.x

McEwen, B. S., & Stellar, E. (1993). Stress and the individual: Mechanisms leading to disease. *Archives of Internal Medicine*, *153*(18), 2093–2101. https://doi.org/10.1001/archinte.153.18.2093

Michaud, P. C., Kapteyn, A., Smith, J. P., & Van Soest, A. (2011). Temporary and permanent unit non-response in follow-up interviews of the Health and Retirement Study. *Longitudinal and Life Course Studies*, *2*, 145–169.

Michaud, P. C., & Van Soest, A. (2008). Health and wealth of elderly couples: Causality tests using dynamic panel data models. *Journal of Health Economics*, *27*(5), 1312–1325. https://doi.org/10.1016/j.jhealeco.2008.04.002

Mullainathan, S., Noeth, M., Schoar, A., 2012. *The market for financial advice: An audit study, Working Paper 17929*. Technical Report. National Bureau of Economic Research.

Noone, P. A. (2017). The holmes–rahe stress inventory. *Occupational Medicine*, *67*(7), 581–582. https://doi.org/10.1093/occmed/kqx099

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Östling, R., Cesarini, D., & Lindqvist, E. (2020). Association between lottery prize size and self-reported health habits in swedish lottery players. *JAMA Network Open*, *3*, e1919713. https://doi.org/10.1001/jamanetworkopen.2019.19713
Pagel, M. (2018). A news-utility theory for inattention and delegation in portfolio choice. *Econometrica*, *86*(2), 491–522. https://doi.org/10.3982/ecta14417
Peress, J., & Schmidt, D. (2021). Noise traders incarnate: Describing a realistic noise trading process. *Journal of Financial Markets*, *54*, 100618. https://doi.org/10.1016/j.finmar.2020.100618
Read, S., & Grundy, E. (2012). Allostatic load–a challenge to measure multisystem physiological dysregulation. Working paper 04/12. Pathways Node at NCRM.
Read, S., & Grundy, E. (2014). Allostatic load and health in the older population of England: A crossed-lagged analysis. *Psychosomatic Medicine*, *76*(7), 490–496. https://doi.org/10.1097/psy.0000000000000083
Sabelhaus, J., Bogdan, M., & Holden, S. (2008). *Defined contribution plan distribution choices at retirement: A survey of employees retiring between 2002 and 2007*. Investment Company Institute.
Sakshaug, J. W., Couper, M. P., & Ofstedal, M. B. (2010). Characteristics of physical measurement consent in a population-based survey of older adults. *Medical Care*, *48*(1), 64–71. https://doi.org/10.1097/mlr.0b013e3181adcbd3
Sanfey, A. G., & Hastie, R. (2000). Judgment and decision making across the adult life span: A tutorial review of psychological research. In D. C. Park & N. Schwarz (Eds.), *Cognitive aging: A primer*. Psychology Press.
Schwandt, H. (2018). Wealth shocks and health outcomes: Evidence from stock market fluctuations. *American Economic Journal: Applied Economics*, *10*(4), 349–377. https://doi.org/10.1257/app.20140499
Seeman, T., Thomas, D., Merkin, S. S., Moore, K., Watson, K., & Karlamangla, A. (2018). The Great Recession worsened blood pressure and blood glucose levels in American adults. *Proceedings of the National Academy of Sciences*, *115*(13), 3296–3301. https://doi.org/10.1073/pnas.1710502115
Shields, G. S., & Slavich, G. M. (2017). Lifetime stress exposure and health: A review of contemporary assessment methods and biological mechanisms. *Social and Personality Psychology Compass*, *11*(8), e12335. https://doi.org/10.1111/spc3.12335
Stephan, Y., Sutin, A. R., Luchetti, M., & Terracciano, A. (2016). Allostatic load and personality: A 4-year longitudinal study. *Psychosomatic Medicine*, *78*, 302.
Tampubolon, G., & Maharani, A. (2018). Trajectories of allostatic load among older Americans and britons: Longitudinal cohort studies. *BMC Geriatrics*, *18*, 1–10. https://doi.org/10.1186/s12877-018-0947-4
Taylor, S. J., & Xu, X. (1997). The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance*, *4*, 317–340. https://doi.org/10.1016/s0927-5398(97)00010-8
The Economist. (2020). Low interest rates leave savers with few good options.
Tobe, S. W., Kiss, A., Sainsbury, S., Jesin, M., Geerts, R., & Baker, B. (2007). The impact of job strain and marital cohesion on ambulatory blood pressure during 1 Year: The double exposure study. *American Journal of Hypertension*, *20*(2), 148–153. https://doi.org/10.1016/j.amjhyper.2006.07.011

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: French, D. (2023). From financial wealth shocks to ill-health: Allostatic load and overload. *Health Economics*, *32*(4), 939–952. https://doi.org/10.1002/hec.4648

APPENDIX

TABLE A1 Results for high blood pressure

	SBP	DBP	Normal BP	Elevated BP	Stage One Hypertension
S&P500 falls × (stock/wealth)	0.466***	0.229**	−0.009**	0.011**	0.009*
	(0.184)	(0.103)	(0.004)	(0.005)	(0.004)

Note: Coefficient estimates for model in Equation (4). Results for *SBP* and *DBP* are as before in Table 2. *Normal BP* is having a SBP lower than 120 mm Hg and DBP lower than 80 mm Hg. *Elevated BP* is having a SBP higher than 120 mm Hg. *Stage one hypertension* is having a blood pressure higher than 130/80 mm Hg. Other controls not displayed: S&P500 level × (stock/wealth); S&P500 return × (stock/wealth), S&P500 falls, S&P500 level, S&P500 return, Stock/wealth ratio, dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Standard errors in parentheses are clustered by household.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

10991050, 2023, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/hec.4648 by Test, Wiley Online Library on [16/05/2023]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License