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Financial wealth shocks and health

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Financial wealth shocks and health

Abstract

A number of 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, we 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. We find that a one standard deviation change in cumulative shocks over a year changes the probability of high blood pressure by 10.2% and the cholesterol ratio by 7.4% of average values for those whose wealth is all in shares. Our findings imply older stock market investors should take account of welfare loss due to stress-related health conditions in managing their portfolio risk.

Keywords: shock, jump, allostatic load, stock market, health

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, we 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. We examine the response of these allostatic load measures to wealth shocks over the previous year.

We 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 (Lee and Mykland, 2008; Bormetti et al., 2015). We find that falls accumulated over one year are associated with higher systolic and diastolic blood pressure as well as with higher cholesterol ratios which are all independent risk factors for cardiovascular disease. On the other hand, recent price movements are statistically insignificant. 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 (Giulietti et al., 2020; Engelberg and Parsons, 2016). Unlike these authors who rely on aggregate population data we 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, we find this variable has no explanatory power for our allostatic load measures in any of our specifications. This reinforces our view that a focus on the cumulative effect of extreme negative events as indicated by the neuroscientific literature better identifies longer-term health impacts on investors.

More broadly, our work contributes to the literature on the wealth-health gradient. Studies have demonstrated large effects on physical health of house price increases (Fichera and Gathergood, 2016); extension of eligibility for state pension (Case, 2004) and lottery winnings (Lindahl, 2005). However, other studies report weak or no evidence (e.g. Michaud and Van Soest, 2008; Carman, 2013; Cesarini et al., 2016) 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

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

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. Our sample of elders is of special interest as older bodies are slower to recover from stress (Read and Grundy, 2012) and are more susceptible to overload due to a lifetime's exposure to stressors (Juster et al., 2010). Since out of the labour market, their wealth and income in retirement 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 (Jones, 2017; Gomes et al., 2021).

Our finding that stock market falls increase allostatic load has a number of implications. First, older stock market investors should take account of 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 and 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). Prolonged or repeated activation of stress responses can lead to sub-clinical *secondary outcomes* which include changes in cardiovascular, metabolic and immune systems (Read and 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 and Grundy, 2012). Primary mediator data is not available in the HRS waves we study² and, in any case, often requires multiple days of collection to provide robust associations (Dowd et al., 2009). Our focus instead is on a number of secondary outcome biomarkers also used in other recent studies (Stephan et al., 2016; Tampubolon and 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 on 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 stock market performance and not an especially stressful event. In contrast, we focus on series of negative financial market shocks using stochastic process theory to identify extreme events. Their cumulative magnitude over time becomes the explanatory variable of interest as, within the threat and harm perspective and consistent with the allostatic load model, each negative event adds to the total stress burden.³

²A 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.

³Accumulating the magnitude of shocks is also motivated by Cohen et al. (2019) who presents evidence that a single event meeting a high criterion for threat may suffice to explain disease risk especially if experienced as overwhelming long afterwards.

3. Data and Methodology

3.1. Data

The Health and Retirement Study (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 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.

Our 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, we 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 and Grundy, 2012). In the HRS, the cardiovascular functioning indicators are systolic and diastolic blood pressure. Metabolic biomarkers are glycosylated hemoglobin (HbA1C), high density lipoprotein cholesterol (HDL), total cholesterol (TC) and cystatin C. The immune system biomarker is C-reactive protein (CRP).⁴ To maintain comparability of results across the different labs used to assay the dried blood spot samples, HRS

⁴ 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.

recommends using the measurement values they adjust to match the distribution of results in a similarly aged nationally representative sample.

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

3.3. Stock market falls

Stock price 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 :

$$\frac{r_\tau}{\sigma_\tau} < \theta \quad [1]$$

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), we divide our raw return $r'_{t,m}$ on day t at time m by a correction factor ζ_m to give r_τ in (1) where

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

i.e. 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 :

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

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 (2) to ensure estimates are free of bias due to observed falls.

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

Data on the Standard and Poor's stock market index of 500 large publicly-traded US companies (S&P500) is provided by Tick Data at tick-by-tick level. We test for falls using 15-minute returns as this frequency was shown by Lee and Mykland (2008) to be high enough for their statistics to achieve adequate power. We also test the robustness of our results to using 5-minute returns. This frequency was recommended by Ferriani and Zoi (2020) to balance a fine data resolution against market microstructure noise.

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 year is determined⁵ :

$$F_{\tau} = \sum_{j=1}^{252 \times 25} |r_{\tau-j}| \times \mathbb{1}\left(\frac{r_{\tau-j}}{\sigma} < \theta\right) \quad [3]$$

The average for the interview date is then determined. We 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). We follow the time span considered in research using major stressful life event checklists where a reference period of one-year is conventional (Cohen et al., 2019).

Dramatic stock market falls may well reflect wider economic and political shocks which affect all individuals. To isolate the shock to financial wealth, we interact our 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. The respondent's stock holdings are the net value of stocks, mutual funds and investment trusts plus the share of IRA/Keogh accounts invested in stocks or mutual funds. Lifetime wealth is calculated as the sum of current net household wealth plus discounted future household income.⁶

⁵Returns at 15-minute intervals during NYSE trading hours (930am to 400pm) for the past 252 trading days in the year are tested.

⁶That is, lifetime wealth, W_{it} , for individual i is:

Selected descriptive statistics are given in table 1. The mean cumulative stock market falls in the year before interview was 13.8% and mean stock holdings to wealth ratio was 6%.

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

$$y_{it} = \beta \frac{S_{it}}{W_{it}} F_t + \delta' \mathbf{X}_{it} + \Theta + \nu_i + \varepsilon_{it} \quad [4]$$

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 ; Θ 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 fraction of wealth in stocks ($\frac{S_{it}}{W_{it}}$) and the sum of all S&P500 falls (F_t) as well as the S&P500 return over the past year, average S&P500 level over the past year and their interaction with the fraction of wealth in stocks. The parameter of interest β is the effect of stock market falls on biomarker levels for those respondents with stock holdings.

4. Results

4.1. Main results

The results of estimating the model in (4) for each of the six allostatic load measures are presented in table 2 for selected variables with full results in table A1. There is a clear statistically significant effect of cumulative stock market falls over the past year on blood pressure and cholesterol for those actually owning shares. The coefficients of $\hat{\beta} = 0.564$ and $\hat{\beta} = 0.222$ indicate that a one standard deviation change in cumulative falls in the S&P500 changes systolic blood pressure by 3.6 mm Hg (2.7% of mean values) and diastolic blood pressure by 1.4 mm Hg (1.8% 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 systolic blood pressure by only 13.7 mm Hg (Tobe et al., 2007). Alternatively, if we repeat the analysis for a dichotomous indicator of

$W_{it} = \text{Wealth}_{it} + \sum_{x=0}^X \text{Income}_x \times \gamma^x \times P(\text{individual } i \text{ survives to year } x)$ 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.

⁷For systolic blood pressure : $0.564 \times 6.38 = 3.6$ and this is $3.6/131.9 = 2.7\%$ of mean values.

For diastolic blood pressure : $0.222 \times 6.38 = 1.4$ and this is $1.4/77.7 = 1.8\%$ of mean values.

high blood pressure we find that a one standard deviation change in cumulative falls in the S&P500 changes the probability of having a blood pressure higher than the threshold for stage 1 hypertension (130/80 mm Hg) by 10.2% (table A2).⁸ Importantly, the interacted S&P500 return and stock ownership variable for which Schwandt (2018) reported a strong relationship with hypertension is not statistically significant in this model or in any alternative specification we considered. This result provides support to our focus on stock market falls in explaining allostatic load changes.

The estimated coefficient of $\hat{\beta} = 0.044$ in the cholesterol model means that a one standard deviation change in stock market falls changes the cholesterol ratio by 0.281 or 7.4% of mean values. Coefficient estimates for the other stress response measures are statistically insignificant but interpretation is complicated by the fact that mediating pathways from event to health outcomes are interconnected, reciprocal and effects can be non-linear (Read and Grundy, 2012). The other financial market variables generally have no substantial relationship with the response measures either when they are interacted with share ownership or applied to all respondents. Two exceptions worth mentioning are that those with higher stock ownership tend to have lower blood pressure perhaps due to a correlation with unobserved health behaviours and that increases in S&P500 levels are seen to reduce four of the six stress measures regardless of stock ownership. The latter result may reflect stock ownership through retirement accounts other than IRA/Keoghs (e.g. 401k plans) or increases in stock market levels may be proxying for some wider socioeconomic health determinant.

The effect sizes we 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 our 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, our focus has been on extreme negative events which both sets of authors acknowledged in sensitivity analysis were driving their key results.

⁸ $0.016 \times 6.38 = 0.102$

4.2. Robustness checks

We undertake a series of checks which confirm the robustness of our 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 year are added to the baseline specification as the effect of our 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 and Iacoviello, 2018) to account for anticipated events which may be correlated with stock market fluctuations and stressful for respondents. Estimates are largely unchanged.

The next set of checks (table 4) demonstrates that the results are robust to alternative specifications of stock market falls. The baseline results are given once again for reference. In the first set of new estimates, equations (1) to (3) are recalculated replacing 15-minute returns by 5-minute returns and the model in (4) then re-estimated. Results are largely the same as before. We then test whether our results are consistent with the allostatic load conceptual model in the next two sets of estimates. The physiological response to stress accumulates gradually over time and therefore a series of recent shocks should not lead 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 day (third set of estimates) or in previous month (last set) and all other *falls over past year*. These two new variables are then also interacted with the fraction of wealth in stocks. It can be seen that stock market falls in the past day are statistically insignificant for each of the allostatic load measures while the previous year's falls remain significant. Findings are similar in the last set of estimates.

Although stock market falls are clearly exogenous, expected health expenses may increase the demand for safer assets implying stock ownership may be endogenous (Pang and Warshawsky, 2010). This is arguably less of an issue in our work. As we consider subclinical biomarker measures before dysregulation has developed into disease, stock holdings $S_{i,t}$ should not be endogenous to changes in these variables unless they coincide with negative tertiary health outcomes. Never-

theless, in this final robustness check, the fraction of wealth in stocks has been determined from stock holdings and lifetime wealth in the previous wave⁹ i.e. $\frac{S_{i,t-1}}{W_{i,t-1}}$. Estimates in table 5 indicate that endogeneity does not appear to be a significant issue. The slight attenuation of estimated coefficients may be simply attributable to inconsistencies in survey responses to wealth questions over time.

4.3. Positive shocks

Repeated stressful events and repeated activations of the stress response over time take a physiological toll on the body. If the allostatic load model is useful in understanding the health response to financial market fluctuations then we should additionally find no effect of positive shocks to financial wealth on our biomarkers. We now return to the baseline specification replacing (1) by

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

The cumulative sum of stock market falls in the previous year (3) then becomes the cumulative sum of all positive shocks to the S&P500 in the previous year. Estimated coefficients are given in table 6 where 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.¹⁰

4.4. Non-response and attrition

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

⁹Non-response leads to the loss of many data points. In the results presented in table 5, missing $S_{i,t-1}$ and $W_{i,t-1}$ values have been replaced by the first available in the sequence : lagged partner's values, last available own value, partner's last available. Results are in fact similar if non-response is ignored (available on request).

¹⁰Schwandt (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 A.11 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.

using proxy respondents to answer on participants' behalf ; by maintaining contact through regular communication and by seeking interviews even after multiple missed waves (Fisher and 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).

Lower participation rates in many surveys with biomesures 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, we augment the model in (4) with a binary selection process s_{it} for those providing measures out of all those eligible for the enhanced interview :

$$y_{it} = \beta \frac{S_{i,t}}{W_{i,t}} F_t + \delta' \mathbf{X}_{it} + \Theta + \nu_{1i} + \varepsilon_{1it} \quad [6]$$

$$s_{it} = \mathbb{1}(\alpha' \mathbf{Z}_{it} + \nu_{2i} + \varepsilon_{2it} > 0)$$

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 7 and are similar to previous estimates.

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, we have shown

¹¹Sakshaug 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 participateded 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.

how stock market participation among American retirees can cause ill health over the longer-term. We find that a one standard deviation change in cumulative falls over a year in the S&P500 changes systolic blood pressure by 3.6 mm Hg (2.7% of mean values) ; diastolic blood pressure by 1.4 mm Hg (1.8% of mean) ; the probability of high blood pressure by 10.2% and the cholesterol ratio by 0.281 (7.4% of mean) for those whose wealth is all in shares. These effects are substantial and are seen to be robust across specifications with additional controls, higher frequency stock market data, adjustments for endogeneity and selection bias. Higher systolic and diastolic blood pressure as well as 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 we have shown how our results are consistent with the allostatic load model for the aetiology of stress-related disease. There are a number of other strengths to our study. We are not reliant on measures of subjective general health status as in most previous studies. We see in our estimates that stock market fluctuations may proxy for wider socio-economic health determinants and that therefore we should be sceptical about results from aggregate studies. Our study instead uses micro-level data on share ownership to establish a relationship. Lastly, we 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). This of course masks considerable heterogeneity and does not reflect more recent developments. There is some evidence that the current environment of low interest rates have encouraged investor risk-taking (The Economist, 2020). Also, the advent of mobile retail brokerage applications will likely increase participation rates further as reductions in information and transaction costs due to new technologies have increased household investment on the stock market in the past (Bogan, 2008).

These effects will also not apply uniformly to all elderly investors. The relationship between

stress and physiological response is complex. Individuals vary in their reactions due to their genetic makeup, life histories, personality and social capital (Read and Grundy, 2012). As any one biomarker level increases, there may also be compensatory changes in other mediating pathways that are dependent on time elapsed and how much change has occurred (McEwen, 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 rebalancing of portfolios away from risky securities as people age is scarce (Guiso and Sodini, 2013).

Retail investors tend to hold highly undiversified portfolios (Gomes et al., 2021). Therefore to reduce exposure to idiosyncratic share price shocks retirees should be encouraged to diversify or invest in mutual funds or make greater use of financial intermediaries. Portfolio managers would also perform the additional role of information stress managers. A common explanation for households' underdiversification as well as inattention to rebalancing opportunities in their retirement accounts is the disutility or displeasure associated with bad news (Ameriks and Zeldes, 2004; Pagel, 2018). On receiving flows of information about bad outcomes information-averse agents put their heads in the sand by reducing portfolio observation and active trading (Andries and Haddad, 2020). We can think of elevation of stress-related biomarkers as an additional aspect of this disutility. Investors become inattentive to information flows as the psychological distress is making them ill.

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

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Tables and Figures

Table 1: Selected descriptive statistics

	mean	s.d.
Allostatic load		
Systolic blood pressure (mm Hg)	131.9	20.8
Diastolic blood pressure (mm Hg)	77.7	11.9
Cholesterol ratio (TC/HDL)	3.81	1.17
Glycosylated hemoglobin (%)	5.97	1.05
Cystatin C (mg/L)	1.24	0.59
C-reactive protein ($\mu\text{g/mL}$)	4.42	8.86
S&P 500 falls in past year (%)	13.80	6.38
S&P 500 level over past year	1481.2	328.3
S&P 500 return over past year	6.37	12.38
Stock holdings to wealth ratio	0.06	0.13
Age	73.03	9.57
Female	0.62	0.49
Race		
White	0.78	0.41
Black	0.17	0.37
Marital status		
Married	0.50	0.50
Divorced	0.12	0.32
Widowed	0.28	0.45
Region		
Northeast	0.15	0.36
Midwest	0.24	0.42
South	0.42	0.49
West	0.19	0.39
Year of interview (%)		
2006	16.85	37.43
2007	0.07	2.66
2008	16.13	36.78
2009	0.01	3.39
2010	13.76	34.45
2011	2.95	16.91
2012	16.32	36.96
2013	5.84	7.62
2014	17.40	37.91
2015	0.10	3.12
2016	13.79	0.34
Number of individuals	12973	
Number of observations	22604	

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

Table 2: Main results

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)	Glyco- sylated hemoglobin	Cystatin C	C-reactive protein
S&P500 falls \times (stock/wealth)	0.564** (0.178)	0.222** (0.098)	0.044*** (0.013)	0.010 (0.008)	0.002 (0.004)	0.064 (0.107)
S&P500 level \times (stock/wealth)	0.004 (0.003)	0.003* (0.002)	-0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.001)
S&P500 return \times (stock/wealth)	-0.074 (0.113)	-0.027 (0.067)	0.004 (0.008)	-0.001 (0.004)	-0.003 (0.002)	0.062 (0.059)
S&P500 falls	-0.194 (0.122)	-0.062 (0.069)	-0.007 (0.008)	-0.005 (0.005)	-0.014*** (0.003)	-0.108* (0.059)
S&P500 level	0.006 (0.007)	0.002 (0.004)	0.003*** (0.001)	-0.000 (0.000)	0.001*** (0.000)	0.010** (0.005)
S&P500 return	-0.017 (0.034)	-0.007 (0.020)	-0.009*** (0.002)	-0.005*** (0.002)	-0.003*** (0.001)	-0.055*** (0.020)
Stock/wealth ratio	-10.823* (5.778)	-6.957** (3.284)	-0.474 (0.420)	-0.152 (0.239)	0.227* (0.126)	-1.060 (2.593)
Within R^2	0.025	0.060	0.054	0.050	0.154	0.014
Number of individuals	12973	12974	11982	11542	12032	12033
Number of observations	22604	22604	18995	20342	20168	20355

Note: Coefficient estimates for model in equation (4). Other controls not displayed : 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 A1. Standard errors in parentheses are clustered by household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)
Baseline	0.564*** (0.178)	0.222** (0.098)	0.044*** (0.013)
+ Household finances	0.541*** (0.179)	0.215** (0.099)	0.046*** (0.013)
+ State of economy	0.550*** (0.178)	0.204** (0.098)	0.046*** (0.013)
+ Economic uncertainty	0.552*** (0.178)	0.218** (0.097)	0.040*** (0.013)

Note: Coefficient estimates for S&P500 falls \times (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 \times (stock/wealth) ; S&P500 return \times (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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results with alternative measures of stock market falls - coefficient estimates for stock market falls interacted with $\frac{\text{stock}}{\text{wealth}}$

	Systolic blood pressure		Diastolic blood pressure		Cholesterol ratio	
	Past year	Recent	Past year	Recent	Past year	Recent
Baseline	0.564*** (0.178)	-	0.222** (0.098)	-	0.044*** (0.013)	-
Falls based on 5-minute returns	0.541*** (0.188)	-	0.227** (0.106)	-	0.046*** (0.014)	-
Falls previous day	0.475** (0.187)	9.682 (6.309)	0.172* (0.103)	5.369 (3.298)	0.050*** (0.014)	-0.622 (0.434)
Falls previous month	0.576*** (0.196)	0.490 (0.565)	0.235** (0.108)	0.128 (0.306)	0.043*** (0.015)	0.053 (0.039)

Note: Coefficient estimates for S&P500 falls \times (stock/wealth) for model in (4). *Baseline* is estimates for falls over past year based on 15-min returns. The next set of estimates are falls over past year based on 5-min returns. In the last two sets of estimates, *Recent* are falls over past day/month based on 15-min returns. *Past year* are falls over past year excluding day/month based on 15-min returns. Other controls not displayed : S&P500 level \times (stock/wealth) ; S&P500 return \times (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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Coefficient estimates for stock market falls interacted with $\frac{\text{Lagged stock}}{\text{Lagged wealth}}$

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)
Baseline ($\frac{S_{it}}{W_{it}}$)	0.564*** (0.178)	0.222** (0.098)	0.044*** (0.013)
Lagged ($\frac{S_{i,t-1}}{W_{i,t-1}}$)	0.539** (0.217)	0.218* (0.119)	0.034** (0.017)

Note: Coefficient estimates for S&P500 falls \times (lagged stock/lagged wealth). Other controls not displayed : S&P500 level \times (lagged stock/lagged wealth) ; S&P500 return \times (lagged stock/lagged 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Results for positive shocks

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)	Glyco- sylated hemoglobin	Cystatin C	C-reactive protein
S&P500 rises \times (stock/wealth)	8.174 (6.124)	1.745 (3.497)	-0.653 (0.505)	-0.264 (0.260)	0.079 (0.136)	0.047 (2.370)

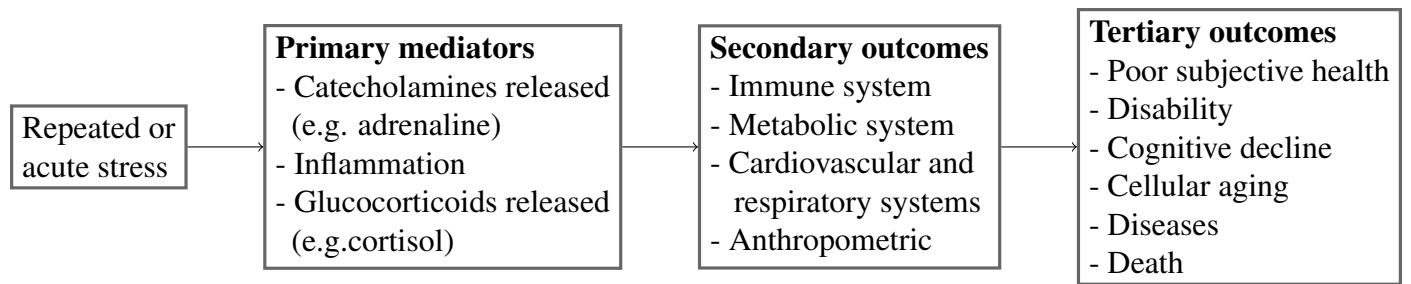
Note: Coefficient estimates for model in (4) with cumulative S&P500 rises over previous year. Other controls not displayed : S&P500 level \times (stock/wealth) ; S&P500 return \times (stock/wealth), S&P500 rises, S&P500 level, S&P500 return, Stock/wealth ratio, dummies for 5-year age band (9), marital status (7), region (3), interview year (10), interview month (11), interview weekday (6). Standard errors in parentheses are clustered by household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Random-effects regression with sample selection - coefficient estimates for stock market falls interacted with $\frac{\text{stock}}{\text{wealth}}$

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)
Baseline	0.564*** (0.178)	0.222** (0.098)	0.044*** (0.013)
With sample selection	0.396** (0.150)	0.149* (0.085)	0.021** (0.009)

Note: Coefficient estimates for model in (6). Other controls in main model: S&P500 level \times (stock/wealth) ; S&P500 return \times (stock/wealth), S&P500 rises, 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). 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). Standard errors in parentheses are clustered by household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Allostatic load model



Source: Adapted from Read and Grundy (2012).

Appendix

Table A1: Main results

	Systolic blood pressure	Diastolic blood pressure	Cholesterol ratio (TC/HDL)	Glyco- sylated hemoglobin	Cystatin C	C-reactive protein
S&P500 falls × (stock/wealth)	0.564*** (0.178)	0.222** (0.098)	0.044*** (0.013)	0.010 (0.008)	0.002 (0.004)	0.064 (0.107)
S&P500 level × (stock/wealth)	0.004 (0.003)	0.003* (0.002)	-0.000 (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.001)
S&P500 return × (stock/wealth)	-0.074 (0.113)	-0.027 (0.067)	0.004 (0.008)	-0.001 (0.004)	-0.003 (0.002)	0.062 (0.059)
S&P500 falls	-0.194 (0.122)	-0.062 (0.069)	-0.007 (0.008)	-0.005 (0.005)	-0.014*** (0.003)	-0.108* (0.059)
S&P500 level	0.006 (0.007)	0.002 (0.004)	0.003*** (0.001)	-0.000 (0.000)	0.001*** (0.000)	0.010** (0.005)
S&P500 return	-0.017 (0.034)	-0.007 (0.020)	-0.009*** (0.002)	-0.005*** (0.002)	-0.003*** (0.001)	-0.055*** (0.020)
Stock/wealth ratio	-10.823* (5.778)	-6.957** (3.284)	-0.474 (0.420)	-0.152 (0.239)	0.227* (0.126)	-1.060 (2.593)
Age: 55-59 years	-1.250 (1.538)	0.084 (0.959)	0.025 (0.123)	0.038 (0.085)	-0.028 (0.036)	0.479 (1.319)
60-64	1.142 (1.916)	2.019* (1.170)	0.105 (0.157)	0.051 (0.107)	-0.042 (0.047)	0.666 (1.390)
65-69	0.347 (2.302)	1.819 (1.383)	-0.016 (0.179)	0.076 (0.122)	-0.066 (0.055)	0.016 (1.520)
70-74	0.948 (2.687)	2.456 (1.597)	0.047 (0.205)	0.136 (0.136)	-0.104 (0.064)	0.066 (1.673)
75-79	-0.009 (3.115)	2.246 (1.832)	0.040 (0.233)	0.164 (0.151)	-0.098 (0.073)	-0.235 (1.844)
80-84	-1.035 (3.566)	2.109 (2.085)	0.010 (0.265)	0.169 (0.168)	-0.105 (0.082)	-0.103 (2.024)
85-89	-3.010 (4.029)	2.004 (2.349)	-0.046 (0.298)	0.173 (0.185)	-0.098 (0.093)	-0.224 (2.203)
90-94	-7.656* (4.622)	1.406 (2.680)	0.020 (0.336)	0.156 (0.205)	-0.064 (0.106)	-0.525 (2.487)
95+	-14.198** (5.761)	-0.506 (3.157)	0.043 (0.388)	0.094 (0.233)	-0.127 (0.127)	0.470 (2.790)
Marital status : Spouse absent	3.317* (1.976)	0.614 (1.054)	-0.135 (0.130)	0.050 (0.096)	0.006 (0.052)	-2.311** (1.164)
Partnered	0.404 (1.799)	0.082 (1.174)	0.090 (0.134)	0.044 (0.081)	0.009 (0.057)	-3.852* (2.161)
Separated	1.240 (2.210)	0.375 (1.262)	-0.029 (0.178)	-0.216 (0.135)	-0.047 (0.061)	-0.913 (1.801)
Divorced	-0.635 (1.501)	-0.787 (0.908)	0.062 (0.119)	-0.131 (0.080)	0.018 (0.035)	-1.478 (0.901)
Separated/divorced	13.384 (12.030)	11.150*** (3.606)	-1.175*** (0.159)	-0.104 (0.222)	-0.171 (0.133)	-1.901 (1.427)

Widowed	1.236 (0.790)	0.088 (0.458)	0.031 (0.053)	-0.077** (0.032)	-0.017 (0.018)	-1.240** (0.509)
Never married	5.437* (3.167)	3.409* (1.920)	-0.565** (0.227)	-0.268** (0.115)	-0.013 (0.073)	-1.075 (0.933)
Region: Midwest	4.982 (3.770)	2.000 (2.291)	0.211 (0.342)	0.312 (0.195)	0.019 (0.074)	-0.852 (1.156)
South	-0.482 (3.465)	-0.237 (2.051)	0.225 (0.264)	0.278 (0.170)	0.030 (0.053)	-0.429 (1.016)
West	2.237 (4.790)	1.258 (2.511)	-0.080 (0.326)	0.445** (0.222)	0.028 (0.083)	0.817 (1.233)
Interview year: 2007	11.222 (9.904)	4.669 (6.539)	0.512 (1.379)	-0.437 (0.308)	-0.222** (0.103)	-6.216*** (2.268)
2008	4.082 (5.627)	7.153** (3.287)	1.915*** (0.396)	-0.170 (0.258)	0.285* (0.148)	8.721** (3.644)
2009	9.582 (8.814)	9.966** (4.721)	2.712*** (0.603)	-1.036 (0.760)	0.330* (0.185)	3.532 (3.636)
2010	3.476 (2.389)	-0.561 (1.367)	0.451** (0.175)	0.129 (0.112)	0.432*** (0.060)	2.863** (1.388)
2011	6.119*** (2.022)	0.259 (1.127)	-0.041 (0.147)	-0.239** (0.095)	0.431*** (0.049)	-2.290 (1.435)
2012	4.848 (6.721)	5.511 (3.931)	2.271*** (0.477)	-0.042 (0.310)	0.637*** (0.175)	11.263** (4.458)
2013	6.572 (5.970)	6.497* (3.416)	2.641*** (0.425)	-0.474* (0.276)	0.583*** (0.160)	7.156** (3.546)
2014	0.966 (3.887)	-3.952* (2.237)	-1.442*** (0.270)	0.371** (0.166)	0.133 (0.095)	-2.927 (2.267)
2015	16.237* (8.840)	0.600 (3.924)	-1.184*** (0.452)	1.824** (0.786)	0.719 (0.626)	-7.850 (5.794)
2016	-1.007 (2.287)	0.817 (1.353)	0.391** (0.168)	0.207* (0.114)	0.029 (0.063)	3.579*** (1.358)
Interview month: February	-0.790 (1.944)	-1.131 (1.140)	-0.196 (0.140)	-0.075 (0.089)	0.033 (0.056)	-1.024 (0.859)
March	-0.175 (1.810)	-0.487 (1.045)	-0.039 (0.139)	-0.318*** (0.088)	-0.089* (0.047)	-3.524*** (1.300)
April	-0.255 (1.911)	-1.317 (1.114)	0.064 (0.152)	-0.419*** (0.092)	-0.134*** (0.049)	-4.969*** (1.451)
May	-0.809 (1.967)	-1.477 (1.142)	-0.021 (0.156)	-0.395*** (0.095)	-0.088* (0.051)	-5.655*** (1.604)
June	-3.171 (1.988)	-2.793** (1.157)	0.135 (0.157)	-0.404*** (0.097)	-0.106** (0.051)	-5.745*** (1.534)
July	-3.991** (2.020)	-3.082*** (1.177)	-0.032 (0.159)	-0.530*** (0.097)	-0.141*** (0.052)	-6.684*** (1.681)
August	-3.638* (2.039)	-2.564** (1.176)	0.083 (0.160)	-0.413*** (0.100)	-0.123** (0.052)	-5.708*** (1.531)
September	-1.870 (2.070)	-2.088* (1.204)	-0.109 (0.162)	-0.579*** (0.101)	-0.159*** (0.054)	-6.051*** (1.606)
October	0.085 (2.177)	-0.739 (1.258)	-0.318* (0.166)	-0.602*** (0.107)	-0.154*** (0.056)	-5.402*** (1.468)
November	0.444 (2.264)	-0.649 (1.335)	-0.444** (0.179)	-0.574*** (0.110)	-0.146** (0.058)	-5.294*** (1.787)
December	2.217	0.008	-0.368*	-0.600***	-0.017	-5.310***

	(2.344)	(1.369)	(0.200)	(0.122)	(0.062)	(1.823)
Interview day: Monday	-0.000	-0.036	0.230***	0.199***	-0.004	0.269
	(0.746)	(0.438)	(0.055)	(0.032)	(0.017)	(0.379)
Tuesday	-1.010	-0.410	-0.236***	0.093***	0.009	0.224
	(0.632)	(0.365)	(0.043)	(0.025)	(0.014)	(0.259)
Wednesday	0.692	0.051	-0.118**	-0.008	0.024	-0.379
	(0.749)	(0.431)	(0.054)	(0.030)	(0.018)	(0.352)
Thursday	-0.386	-0.168	0.023	0.137***	0.032**	0.349
	(0.687)	(0.395)	(0.051)	(0.029)	(0.016)	(0.313)
Friday	0.054	-0.357	0.029	0.055**	0.053***	-0.034
	(0.648)	(0.375)	(0.048)	(0.027)	(0.015)	(0.304)
Saturday	-0.048	-0.046	0.006	0.150***	0.042**	0.399
	(0.699)	(0.405)	(0.053)	(0.030)	(0.016)	(0.389)
Constant	123.798***	73.033***	-0.483	6.349***	0.102	-5.748
	(11.812)	(6.885)	(0.856)	(0.546)	(0.313)	(7.335)
Within R^2	0.025	0.060	0.054	0.050	0.154	0.014
Number of individuals	12973	12974	11982	11542	12032	12033
Number of observations	22604	22604	18995	20342	20168	20355

Note: Fixed effect regressions. Standard errors are clustered by household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Results for high blood pressure

	Systolic blood pressure	Diastolic blood pressure	High blood pressure
S&P500 falls \times (stock/wealth)	0.564*** (0.178)	0.222** (0.098)	0.016*** (0.005)
Within R^2	0.025	0.060	0.018
Number of individuals	12973	12974	12973
Number of observations	22604	22604	22603

Note: Coefficient estimates for model in (4). Results for *Systolic* and *Diastolic blood pressure* are as before in table 2 and table A1. *High blood pressure* is having a blood pressure higher than the threshold for stage 1 hypertension (130/80 mm Hg). Other controls not displayed : S&P500 level \times (stock/wealth) ; S&P500 return \times (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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$