Effects of Health Care Policy Uncertainty on Households' Portfolio Choice*

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Abstract

This paper conducts an empirical analysis of the effect of health care policy uncertainty (HCPU) on households' portfolio choice. A causal identification approach is developed, whose key assumption is the existence of an exogenous variable that shifts responsiveness to HCPU without shifting responsiveness to other macroeconomic time series. Combined with the assumption of risk averse agents, this approach results in an informative bound on the average causal effect of HCPU. The empirical results highlight the importance of HCPU as a determinant of households' financial behavior, and showcase substantial heterogeneity in HCPU effects across varying unexpected changes to health.

JEL codes: D14, D80, I18, C21, C14.

Keywords: Health and Retirement Study (HRS), Household Finance, Partial Identification, Heterogeneous Effects, Semiparametric Estimation

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I. Introduction

More than a decade after the 2010 enactment of the Affordable Care Act, health care policy remains a central topic of political debate in the United States. In a comparison of 11 policy categories, Baker et al. (2016) find health care policy to be the second largest source of policy uncertainty in the US, behind only fiscal policy uncertainty. The recent COVID-19 pandemic has driven both economic and health care policy uncertainty to unprecedented levels, nearly double their pre-2020 levels, as countries scrambled to determine an appropriate response to an unknown and rapidly evolving threat (Altig et al., 2020). Yet the literature on the economic effect of uncertainty about health care policy on households' economic behavior is in its infancy. This paper is among the first to consider health care policy uncertainty as a driver of household investment decisions. The results shed light on the portfolio choice of households and attach economic costs to the uncertainty surrounding future health care policy.

A key challenge in the context of policy uncertainty is the identification of causal effects due to the potential confoundedness with other macroeconomic variables. For example, Bloom (2014) notes that the (general) economic policy uncertainty index of Baker et al. (2016) is 51% higher in recessions. Simple identifying assumptions such as independence are thus rarely plausible in such macroeconomic contexts. An additional complication arises because policy uncertainty associated with federal policy that comes into force on a specific date is time-invariant across households. As a result, standard alternative identifying assumptions such as parallel trends are not applicable. To address this challenge, the literature focuses on the analysis of sub-populations that are expected to differ in their responsiveness to the specific policies but to react similarly to other forms of uncertainty, such as recession-caused economic uncertainty.[1]

[1] For example, Giavazzi and McMahon (2012) compare private sector employees with civil servants in their analysis of Germany's 1998 national election, arguing the latter were not directly affected by the candidates' policy differences and hence less exposed to the increased policy uncertainty. Similarly, Baker et al. (2016) consider a regression specification that interacts policy uncertainty with a measure of revenue from government contracts to capture firms' heterogeneous exposure to uncertainty in government spending.

Motivated by the idea that subgroup heterogeneity may be used to aid causal identification, we develop a two-step approach for deriving a bound on the average causal effect of health care policy uncertainty that combines differences in health care policy uncertainty effects across subgroups with the assumption of risk averse agents. We show that the resulting bound on the average effect is identified without (conditional) independence assumptions typically placed on the macroeconomic variable of interest. Instead, the key identifying assumption is that there exists an exogenous variable that shifts responsiveness to the (endogeneous) macroeconomic variable of interest, but does not shift responsiveness to other macroeconomic time series. This paper thus provides a novel approach for causal identification in the context of macroeconomic variables and their effects on microeconomic outcomes.

The first stage of the developed approach targets the average difference in effects of health care policy uncertainty across subgroups with (potentially) varying responsiveness. This paper uses unexpected changes in households' health to capture households' heterogeneous responsiveness to health care policy uncertainty. The changes are constructed under the assumption that households' health expectations are reasonably approximated by a linear first-order Markov process.[2] The strategy to exploit health heterogeneity is motivated by the idea that worsening health expectations may affect households' exposure to medical expenditure risk as induced by health care policy uncertainty. While primarily used as a building-block for the construction of the bound on the (unconditional) average causal effect of health care policy uncertainty, the first stage parameters also shed light on heterogeneous responses of households to health care policy uncertainty that depend on unexpected changes in health (both better-than-expected or worse-than-expected) and may thus be of interest per se. For example, this relative distribution of effects may have important consequences regarding the socio-economic disadvantage associated with bad health in the US (e.g., Smith, 1999): a positive association between an uncertainty-caused shift into safe assets and unexpected health decline widens the portfolio divide.

[2]This approach is similar to Wu (2003) and Berkowitz and Qiu (2006), who construct quasi-random shocks on a panel of individuals using information on severe health conditions.

The second stage of the approach uses the assumption of risk averse agents to bound the conditional causal effects of health care policy uncertainty. In particular, we leverage economic theory on background risk, which implies that risk averse households will (weakly) decrease their relative demand for risky assets when faced with an undiversifiable risk such as increased health care policy uncertainty (Pratt and Zeckhauser, 1987; Kimball, 1993; Gollier and Pratt, 1996). In combination with the identified average difference in health care policy uncertainty effects across subgroups from the first step, we show that the assumption of risk aversion allows for partial identification of the average causal effect of health care policy uncertainty on households' portfolio choice.

This paper primarily draws from and contributes to four strands of literature. First, it uses as a starting point the category-specific health care policy uncertainty index developed by Baker et al. (2016) as the primary variable of interest. Existing literature on policy uncertainty has largely focused on policy uncertainty's association with other macroeconomic variables (e.g., Stock and Watson, 2012) or its effects on firms (e.g., Pástor and Veronesi, 2013; Baker et al., 2016; Gulen and Ion, 2016). This paper contributes to the burgeoning strand of literature that instead analyzes the effects of policy uncertainty on households, including Giavazzi and McMahon (2012), Luttmer and Samwick (2018), as well as the working papers of Agarwal et al. (2018) and Gábor-Tóth and Georgarakos (2019). To the best of our knowledge, ours is the first study with a focus on health care policy uncertainty, despite the prominence of health care in the US policy landscape.

Second, this paper contributes to the literature on the economic consequences of bad health and exposure to medical expenditure risk. The identification strategy we employ is motivated by linkages between background risk and worsening health. Our analysis of heterogeneous responsiveness to health care policy uncertainty with respect to unexpected changes in health complements existing analyses on the unconditional effects of health and medical expenditure risk on households' portfolio choice (e.g., Goldman and Maestas, 2013; Hugonnier et al., 2013; Ayyagari and He, 2017). The results provide empirical insights into the opposing mechanisms of household-decision making in the context of health shocks: on one hand, increased relative demand for safe assets due to the background risk induced by higher expected health care costs, on the other, decreased overall risk aversion due to reductions in life expectancy and expected utility derived from consumption (Smith, 1999).

Third, we add to the literature on identification of causal parameters in macroeconomic settings. Most closely related are the increasingly popular shift-share designs, where macroeconomic (common) shocks are interacted with a measure of individual-level exposure (e.g., Adao et al., 2019; Goldsmith-Pinkham et al., 2020). The approach presented here differs from existing literature by providing a nonparametric identification result rather than relying on multiplicative-interaction specifications derived from accounting identities considered in conventional shift-share designs. To the best of our knowledge, our approach also provides a novel partial identification result in the context of exogenous exposure to endogeneous shocks.

Fourth, we highlight the advantages of recent advances in semiparametric estimation of heterogeneous effects via a novel setting. An estimator of the derived bound on the average causal effect of health care policy uncertainty is constructed based on the generalized random forests of Athey et al. (2019). This semiparametric approach allows for flexible nonlinear estimation of the interaction between unexpected changes in health and health care policy uncertainty, thus avoiding stronger ex ante functional form assumptions that plague linear multiplicative-interaction specifications. Our application of Athey et al. (2019) differs from previous approaches in that it neither rests on identification through a conditional independence assumption of the variable of interest nor on availability of a valid instrument.[3]

The empirical results indicate economically substantive average causal effects of health care policy uncertainty on households' portfolio choice. When health care policy uncertainty increases by 70%, couple (single) households are estimated to increase their safe asset share by *at least* 3.5 (2.7) percentage points.[4] The same increase in health care policy uncertainty

[3]See, for example, Davis and Heller (2020) for an application of a random forest-based procedure for estimating crime reductions from summer job programs conditional on individual characteristics.

[4]These interpretations are made precise in Section VI. For illustrative purposes, throughout the paper we refer to an increase of 70% in health care policy uncertainty, corresponding to the increase in the Baker et al. (2016) health care policy uncertainty index from a 2016 average of 110 to the 2017 average of 191. The latter year is associated with extensive political efforts to repeal the Affordable Care Act.

also results in an estimated average decrease in couple (single) households' risky asset share of at least 1.5 (2.3) percentage points. The results thus highlight the importance of health care policy uncertainty as a determinant of households' financial behavior.

Complementing the empirical results on the unconditional average causal effects of health care policy uncertainty, our first stage estimates indicate strong heterogeneity with respect to unexpected changes in health in the effect of health care policy uncertainty on households' relative demand for safe and risky assets. Compared to a couple (single) household that finds itself with fewer severe health conditions than expected, a couple (single) household that experiences no unexpected change in severe conditions is estimated to increase its safe asset share by approximately 3.3 (3.1) percentage points, on average, when health care policy uncertainty increases by 70%. Correspondingly, the relative risky asset share reduction of couple (single) households is approximately 2.9 (2.2) percentage points. Differences in the effect of health care policy uncertainty of similar magnitude are also documented across households that differ by unexpected changes in the number of hospital stays or ability to conduct activities of daily living.

In addition to documenting heterogeneity per se, our first stage estimates indicate nonlinearities in how health changes households' responsiveness to health care policy uncertainty. In particular, households that are at their expected health level are estimated to react more strongly to increases in health care policy uncertainty than households that are in substantially better or worse health than expected. This non-monotonicity in point-estimates suggests that as unexpected changes in health become increasingly worse, the background risk mechanism induced by higher expected health care costs is attenuated by the reduction in life expectancy and utility derived from consumption.

The paper proceeds as follows: Section II reviews relevant literature. Section III describes the data. Section IV provides the nonparametric identification results. Section V discusses estimation. Section VI presents the empirical results. Section VII discusses implications with some suggestions for future research. A series of supplemental appendices describing data construction, methodological details, and robustness checks is available online.

II. Literature Review

Our analysis builds on recent studies on the implications of policy uncertainty for households' economic behavior, theoretical and empirical work on portfolio choice in the context of income risk, and empirical research on the effect of health and medical expenditure risk on financial decisions of individuals. This section discusses each in turn.[5]

Existing studies on the microeconomic effects of general policy uncertainty suggest adverse effects on households' consumption and risky asset shares. Investigating Germany's 1998 national election, Giavazzi and McMahon (2012) estimate an increased savings rate of non-civil servants in the wake of increased policy uncertainty. Aaberge et al. (2017) corroborate the positive effect of policy uncertainty on households' savings by exploiting a major political shock in China. The ongoing work of Agarwal et al. (2018) and Gábor-Tóth and Georgarakos (2019) suggests that general policy uncertainty decreases households' relative demand for risky assets.

Insights regarding relevant mechanisms can be drawn from models on precautionary savings and background risk, both of which have been extensively analyzed in the context of income uncertainty. Savings behavior unaccounted-for by conventional life cycle models was first explained by 'buffer-stock' models (e.g., Kimball, 1990) that predict consumption to be not only related to expected income, as predicted by the life cycle model, but also to higher moments such as income variance. The literature on background risk formalizes households' portfolio choice in an environment of multiple risks. Pratt and Zeckhauser (1987), Kimball (1993), and Gollier and Pratt (1996) provide definitions of risk aversion which imply that households that are exposed to an undiversifiable risk are less willing to bear other types of risk, including rate-of-return risk. Supporting empirical evidence is provided by, for example, Guiso et al. (1996), who find that income uncertainty decreases the demand for risky financial assets.

[5]An earlier version of the paper also presented a toy model on portfolio choice of heterogeneous agents in the presence of health care policy uncertainty. As the insights are largely reflected in previous literature, the model is omitted here and we instead refer the interested reader to Wiemann and Lumsdaine (2019).

Why might health care policy uncertainty affect the financial behavior of households in a similar manner to income uncertainty? As insufficient health care coverage can magnify the large out-of-pocket medical expenditures that frequently accompany health shocks, health care policy uncertainty could present greater spending needs with potentially similar implications as income risk. Such increased medical expenditure risk has been shown to reduce relative demand for stocks in the context of insurance coverage-caused medical expenditure risk (Goldman and Maestas, 2013). Although related to insurance-coverage-caused-risk in its implictions for portfolio choice, health care policy uncertainty is a distinct source of risk. In particular, although households can affect their own insurance coverage (e.g., through private insurance plans), they cannot meaningfully influence the national debate on health care reform. Therefore, analyzing macroeconomic health care policy uncertainty alleviates endogeneity concerns arising from the positive associations between households' medical expenditure risk exposure and their wealth or education.[6] But, as noted in the introduction, it also introduces concerns about potential confoundedness with other macroeconomic sources of uncertainty (Bloom, 2014). As economic contractions are linked to higher economic uncertainty and lower investment prospects, the omission of these other macro sources of uncertainty in our specification could lead to over-estimated effects of policy uncertainty. Such concern applies to the analysis of policy uncertainty generally and is not specific or unique to our health care policy uncertainty application.[7]

The potential entanglement of health care policy uncertainty with other macroeconomic variables motivates an alternative approach that does not directly target the unconditional

[6]As higher wealth and education imply higher investment in risky assets and more accumulated wealth, accurate analysis of the isolated effect of medical expenditure risk defined using health coverage requires plausibly exogenous variation, for example, in subsidized health insurance eligibility (e.g., Goldman and Maestas, 2013).

[7]Health care policy uncertainty may even be expected to be *less* confounded by economic uncertainty than other types of policy uncertainty, at least historically. For example, in contrast to the fiscal policy analogue, the enactment of counter-cyclical health care policy measures to combat economic downturns was rare prior to the COVID-19 pandemic.

causal effect of health care policy uncertainty and instead analyzes relative effects, specifically: *Given an increase in health care policy uncertainty, how do expected changes in households' risky asset share vary with household's health?* As will be discussed in Section IV, quantifying these relative causal effects does not require a conditional independence assumption for health care policy uncertainty. Insights into the microeconomic consequences therefore can be achieved without the frequently implausible assumptions necessary for the identification of absolute causal effects of macroeconomic time series such as policy uncertainty.

Existing literature suggests two key mechanisms that drive differences in susceptibility with respect to households' health. First, a background risk mechanism that associates worsening health with increased expected medical expenditures. Evidence for such a mechanism is provided by Atella et al. (2012), who find that health shocks have a negative effect on demand for risky assets in European countries without universal health care but find no evidence of an effect in other European countries. Second, bad health may lower households' expected lifespan and consumption utility (Smith, 1999). These opposing mechanisms can make interpretation of mixed-empirical results regarding the effects of health measures on portfolio choice challenging (e.g., Rosen and Wu, 2004; Berkowitz and Qiu, 2006; Edwards, 2008; Love and Smith, 2010). This paper's empirical analysis also provides insights into the tradeoff between the two mechanisms in the context of health care policy uncertainty.

III. Data

This section describes the data and the construction of the variables on unexpected changes in health. After an overview of the household variables, Baker et al.'s (2016) health care policy uncertainty index is illustrated.

A. Household Data

The unit of analysis is the household. The household data come from the Health and Retirement Study (HRS), a biennial comprehensive, nationally representative longitudinal panel of noninstitutionalized US residents over age 50. The older population is a particularly relevant sample of the US population due to its large share of total wealth and financial asset investment, as emphasized by the vast literature using the HRS for analysis of portfolio choice (e.g., Rosen and Wu, 2004; Goldman and Maestas, 2013). It is also the population for whom health care policy uncertainty is likely to be particularly salient, as individuals in the second half of their lives approach decreasing income, wealth decumulation and declining health. The consumption and financial behavior of these sample households is thus likely to have broader macroeconomic implications.

We omit the first wave of the HRS due to differences in important health variables and use the remaining eleven waves (1994-2014).[8] We use the user-friendly versions of the HRS available as the RAND HRS Longitudinal File 2014 which contain imputations for missing data including financial asset holdings.[9] Supplemental Online Appendix A provides the corresponding data citation along with those of the other data sources used for this paper.

Portfolio Choice and Financial Variables. For analyzing households' financial behavior and portfolio choice, we first follow the strategy of Rosen and Wu (2004) to collapse financial assets into four categories: safe assets (checking and savings accounts, CDs, government savings bonds and T-bills), risky assets (stocks and mutual funds), bonds, and IRA retirement accounts. This paper focuses primarily on the shares of risky and safe assets (i.e., the first two of these four categories) because the IRA account information in the HRS does not allow for sufficiently detailed risk-classification and only a small fraction of financial wealth is held in bonds.[10] Further, shares of financial assets are calculated over total financial wealth rather than all assets, as non-liquid wealth (e.g., housing wealth) is not readily adjustable to changes in background risk (Goldman and Maestas, 2013).

[8]Specifically, wave one of the HRS does not provide comparable measures to the rest of the waves for the "activities of daily living" and "instrumental activities of daily living" measures.

[9]As a condition of use, we note that: "The HRS is sponsored by the National Institute on Ageing (grant number NIA U01AG009740) and is conducted by the University of Michigan."

[10]The HRS does contain information on the asset composition of financial wealth in the five most recent waves. However, because the empirical approach relies on temporal variation in health care policy uncertainty, omitting the earlier waves noticeably reduces statistical power. This paper's separate consideration of risky asset investments outside of retirement accounts is in line with existing literature, which points out that IRA assets may be relatively illiquid for some households (e.g., due to costs of adjusting retirement portfolios) and may suffer from measurement error, see, for example, Rosen and Wu (2004) and Love and Smith (2010).

Health Shocks. A suitable measure of unexpected changes in health status is needed to adequately assess potential heterogeneity in the susceptibility to health care policy uncertainty. Empirically, health is an intrinsically unobserved variable but a variety of proxies have been suggested in previous research (Currie and Madrian, 1999).

Many studies (including the HRS) assess health using survey respondents' answer to a self-reported question of the form "Would you say your health in general is (1) excellent, (2) very good, (3) good, (4) fair, or (5) poor?" Self-reported health measures such as this 5-point Likert scale variable are frequently used as proxies for health (e.g., Rosen and Wu, 2004), yet, some doubts remain about the role of potential reporting bias (e.g., Lumsdaine and Exterkate, 2013).

As an alternative, some studies have employed more objective measures of health. For example, Wu (2003) and Berkowitz and Qiu (2006) construct exogenous health shocks given by severe health conditions reported between survey waves. These shocks are defined by a diagnosis of diabetes, lung disease, cancer or malignant tumor growth, or experiencing a stroke or heart problems.[11] Other frequently-used measures are the proxies given by self-reported limitations in Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs). Five and three of these, respectively, are asked of the respondents in the HRS, capturing possible impairments of respondents to (1) bathe, (2) eat, (3) dress, (4) walk across a room and (5) get in and out of bed, as well as (1) use a telephone, (2) take medication, and (3) handle money. To complement these measures of physical ability, Fan and Zhao (2009) consider a separate variable to capture a respondents' mobility, summing indicators that are equal to one if the respondent has difficulty (1) walking one block, (2) sitting for two hours, (3) getting up from a chair, (4) climbing a flight of stairs, (5) stooping or kneeling, or (6) lifting and carrying 10 lbs.

Lack of consensus as to which proxy is preferable in the literature motivates a flexible approach. We construct quasi-random health shocks from the available data under the assumption that households' health expectations are reasonably approximated by a linear

[11]'Mild' conditions such as high blood pressure and arthritis also are reported in the HRS. Following the literature, they are not included in the analysis.

first-order Markov process. This approach is a relaxation of the first-difference construction of health shocks as in Wu (2003) and Berkowitz and Qiu (2006) as it allows for simultaneous consideration of multiple health proxies as well as heterogeneous health expectations conditional on observed household characteristics. In addition, it addresses the need to condition on known determinants of health, such as education (e.g., Lleras-Muney, 2005). Using a VAR that simultaneously considers all health variables, we estimate

$$H_{it} - AH_{it-1} = BX_{it} + \varphi_{it}, \tag{1}$$

where $H_{it} \in$ is a 5×1 vector of integers capturing (a) a household's self-reported health measure, (b) the number of limitations reported in the HRS' ADL and IADL measures, (c) the cumulative (from the beginning of the sample to time t) number of severe health conditions, (d) the current number of limitations to mobility, and (e) the number of nights spent in a hospital during the previous two years, and A and B are respectively 5×5 and $5 \times k$ matrices of fixed and unknown coefficients, where k is the number of included household characteristics. Under a rational expectation assumption, the 5×1 vector of residuals, φ_{it} is then interpreted as an approximation to an unexpected change in the various components of a household's health.

We follow earlier literature and analyze single and couple households separately (e.g., Wu, 2003; Rosen and Wu, 2004; Berkowitz and Qiu, 2006; Love and Smith, 2010), and for couple households define the health measures introduced above as the maximum value across spouses (e.g., Coile and Milligan, 2009; Love and Smith, 2010). The $k \times 1$ set of household characteristics, X_{it}, are a household's age as well as dummy variables for five educational attainment categories, race categories (described below), and wave-specific wealth and income quartiles. Gender is also included when analyzing single households. For couple households, the controls for the attained education and age are constructed as the maximum of both spouses, and six race dummy variables are included, based on all possible combinations of the three categories "White," "Black", and "Other" across the two spouses. The purpose of the inclusion of these controls in the linear first-order Markov approximation of households' health expectation is to address primary concerns regarding conditional heterogeneity in changes in health. The constructed residuals are orthogonal to the included controls and thus account for possible mechanisms such as a decrease in health with age and associations between health developments and socio-demographic characteristics.

Note that the dependent variables H in (1) are integer-valued ordinal variables so that the linear residualization procedure by construction is intended to act only as an approximation to households' health expectation.[12] As a consequence, the constructed unexpected changes in households' health, φ, also should only be interpreted ordinally. While the linear functional form restrictions on the constructed variables would thus make linear regression estimates difficult to interpret, the semiparametric estimation approaches illustrated in Section V, which are invariant to monotonic transformations of the explanatory variables, are well suited for ordinal variables of this nature.[13]

Final Analysis Sample. We remove those households that have no positive holdings of financial assets, are missing one or more of the above variables, or only occur in a single wave, leaving an analysis sample of 45,384 single and 57,190 couple household-wave observations. Supplemental Online Appendix B provides detailed documentation of the cleaning steps and the associated reduction in sample at each stage, as well as complementary summary statistics of household characteristics.

B. Measuring Health Care Policy Uncertainty

Baker et al. (2016) develop a computer-driven, news-based economic policy uncertainty index, based on the proportion of articles with the word triplets "uncertain", "economic", and "policy" (and their synonyms) in ten major newspapers in the US. The economic policy uncertainty index has been shown to be well representative of policy uncertainty in Baker et al. (2016), and has since been used in a vast amount of policy uncertainty literature, in particular to examine the effect of policy uncertainty on firms (e.g., Bloom, 2014) and on macroeconomic time series (e.g., Stock and Watson, 2012). To the best of our knowledge,

[12]For example, a self-reported health of two ("very good") should not be interpreted as being twice as good as a self-reported health of four ("fair").

[13]In interpreting the results, we further avoid comparisons across numerical values of φ and instead focus on differences across percentiles of its empirical distribution.

this paper is one of the earliest to apply Baker et al.'s (2016) policy uncertainty indices in a study of households.

Fortunately for our examination of health care policy uncertainty, Baker et al. (2016) developed not only a general economic policy uncertainty index but also several categorical indices, constructed using the Access World News newspaper archive of about 1,500 US papers. Among these is a health care policy uncertainty index, capturing the frequency of articles that feature the above word triplets as well as at least one term related to health care such as "Medicaid", "health insurance" or "Obamacare".[14] Figure 1 shows the health care policy uncertainty index between 1992 and 2017, and its average over the preceding 12 months. The average is characterized by four substantive increases that can be linked to health care policy efforts in the US. Note that the health care efforts of the Trump administration are not considered for estimation, as the HRS sample only provides observations up-to and including 2015. We merge the household data with the 12-month average preceding the end date of the month of each individual's/household's HRS interview.

[Figure 1 about here.]

IV. Identification

This section shows that a bound on the average causal effect of health care policy uncertainty (HCPU) can be identified by combining the assumption of risk averse agents with differences in the effect of health care policy uncertainty across subgroups. After introducing the empirical setup, we derive a point identification result for the relative differences in HCPU effects.[15] The section concludes by combining the identified differences with an assumption of risk averse agents to obtain the desired bound on the average causal effect of health care policy uncertainty.

[14]Additional terms are "health care", "Medicare", "malpractice tort reform", "malpractice reform", "prescription drugs", "drug policy", "food and drug administration", "FDA", "medical malpractice", "prescription drug act", "medical insurance reform", "medical liability", "part d", and "affordable care act."

[15]Although an explicit discussion of these parameters or their identifying assumptions is typically omitted, differences in the causal effects of general economic policy uncertainty have been considered in previous literature, as noted earlier (e.g., Baker et al. (2016) and Giavazzi and McMahon (2012)). The more formal discussion of the estimand in the context of heterogeneous uncertainty exposure presented here may

A. *Point Identification of Differences in Conditional Causal Effects*

A standard approach to identification relates the causal effect of a scalar variable of interest $X \in \mathcal{X}$ to a scalar outcome $Y \in \mathcal{Y}$. Following the conventional latent variable notation, let $Y = \tilde{g}(X, U)$ where $U \in \mathcal{U}$ are unobserved determinants of Y of unknown dimension and $\tilde{g} : \mathcal{X} \times \mathcal{U} \to \mathcal{Y}$ is an unknown structural function.[16] A key parameter of interest is the difference in the average structural function evaluated at two hypothetical states of the variable of interest, which we refer to as the average causal effect (ACE):

$$\text{ACE}(x', x) \quad \equiv \quad E\left[\tilde{g}(x', U) - \tilde{g}(x, U)\right], \tag{2}$$

$\forall x', x \in \mathcal{X}$ where the expectation is with respect to U.[17] Here and throughout, we implicitly assume existence of all needed moments. Because U is unobserved, the ACE as defined in (2) is not identified from the data without additional assumptions.

In our application, Y denotes the household's safe or risky asset share and X denotes health care policy uncertainty. As noted previously, when the variable of interest is a macroeconomic variable such as health care policy uncertainty, assumptions often invoked for identification of the ACE, such as independence or conditional independence of X and U, are rarely plausible due to the confounding by other macroeconomic variables as represented in U. Disentangling the effect of health care policy uncertainty from these other confounders is exacerbated by the absence of cross-sectional macroeconomic variation at each time period, which prevents the use of conventional difference-in-difference estimators. Specifically,

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contribute to a better understanding of empirical results from past and future studies on the microeconomic implications of policy uncertainty. For additional prominent examples from the the policy uncertainty literature, see Pástor and Veronesi (2013) and Gulen and Ion (2016).

[16]As X and U define Y deterministically, this specification is also referred to as the "all causes" model (see, e.g., Heckman and Vytlacil, 2007). Note further that the latent variable notation is equivalent to potential outcome notation.

[17]In the context where X can directly be manipulated (for example, enrollment in a jobs training program), and where $\mathcal{X} = \{0, 1\}$, the parameter defined in (2) is frequently referred to as the average *treatment* effect (ATE). We prefer the slightly more general terminology "average causal effect" to highlight that the variable of interest in this paper is macroeconomic in nature, which is not typically thought of as a "treatment".

differences in uncertainty levels cannot be exploited because HCPU is an aggregate variable that is constant for everybody at a specific point in time and hence perfectly collinear with time-fixed effects. Therefore, we turn to differences in responsiveness to uncertainty in order to gain an understanding of the effect of health care policy uncertainty on households.

To formally define the resulting parameter, consider an observed, possibly vector-valued variable $H \in \mathcal{H}$ that may affect the responsiveness of households to the variable of interest X. Letting $Y = g(X, H, U)$, it is useful to first define the conditional average causal effect (CACE) as

$$\text{CACE}(x', x, h) \quad \equiv \quad E\left[g(x', h, U) - g(x, h, U)\right], \tag{3}$$

$\forall x', x \in \mathcal{X}, h \in \mathcal{H}$. As before, the expectation is with respect to the unobserved U. The CACE gives the expected difference in outcomes under two hypothetical states (x', x) for an arbitrary household in the population, conditional on $H = h$. The difference in conditional average causal effects (DACE) is then given by

$$\text{DACE}(x', x, h', h) \quad \equiv \quad \text{CACE}(x', x, h') - \text{CACE}(x', x, h), \tag{4}$$

$\forall x', x \in \mathcal{X}, h', h \in \mathcal{H}$. The DACE gives the difference in CACE under two hypothetical states of the variable H for an arbitrary unit in the population.[18]

Motivated by the theoretical arguments discussed in Section II that illustrate how background risk considerations regarding future health care expenditures may be magnified by sudden changes in health, we consider the heterogeneity-invoking variable H to be exogenous health shocks, that is, deviations from a household's expected health. The DACE is then informative about the conditional distribution of health care policy uncertainty effects with respect to these unexpected changes in health.

Note that the DACE cannot provide evidence on the absolute effects of health care policy uncertainty without additional assumptions. While the conditional difference of average

[18] Although at first glance this formulation resembles a difference-in-difference design, note that it represents an important generalization in two key ways. First, exposure to "treatment" (here: uncertainty) is not necessarily governed by time. Second, it allows for the absence of a group of untreated individuals.

causal effects is identified, the individual CACEs are, in general, not. Using only the DACE, it is therefore not possible to assess the sign or magnitude of the average causal effect of the macroeconomic variable X on the outcome Y. In some contexts, however, prior knowledge about the *level* of the conditional average causal effect for a particular value of the heterogeneity-invoking variable may be available. This additional knowledge would suffice for pinning down the location of the conditional distribution of causal effects and allows for identification of the (absolute) average causal effect of health care policy uncertainty. As will be discussed in the next subsection, the assumption of risk averse agents suffices for providing a bound on the ACE of health care policy uncertainty on households' portfolio choice.

The assumptions necessary for nonparametric identification of the DACE differ from those of the ACE or the CACE. A set of sufficient assumptions for the nonparametric identification of the DACE$(x', x, h', h), \forall h', h \in \mathcal{H}$, is given by

A1. $H \perp\!\!\!\perp U$ (H-exogeneity),

A2. $\{g(\tilde{x}, h', U) - g(\tilde{x}, h, U)\}_{\tilde{x} \in \{x', x\}, h, h' \in \mathcal{H}} \perp\!\!\!\perp X$ (Exogenous response heterogeneity),

A3. $f_{XH}(\tilde{x}, h) > 0, \quad \forall \tilde{x} \in \{x', x\}$ and $h \in \mathcal{H}$, where f_{XH} denotes the joint pdf or pmf (Sufficient overlap).

Under these assumptions, the DACE is point identified in the sense of Hurwicz (1950). Supplemental Online Appendix C provides the derivations to show that

$$\begin{aligned} \text{DACE}(x', x, h', h) =& (E[Y|X = x', H = h'] - E[Y|X = x, H = h']) \\ & - (E[Y|X = x', H = h] - E[Y|X = x, H = h]), \end{aligned} \tag{5}$$

where the conditional moments on the right hand side can be directly estimated from the data.[19]

[19]Note that precise interpretation of estimates of the ACE, CACE, and DACE depends on the specific population studied. As highlighted in Section III, the dataset used in this paper is a representative sample of noninstitutionalized US residents over age 50 in the years 1994-2014.

Note that identification of the DACE is achieved without assuming (conditional) independence of health care policy uncertainty. Instead, the key assumptions are (**A1.**) the random assignment of the heterogeneity-invoking variable – unexpected deviations from expected health – across households and time, and (**A2.**) that the associated response heterogeneity is not associated with other macroeconomic variables. The first is analogous to the setting of exogenous exposure to endogeneous shocks, commonly considered in shift-share design applications (see, e.g., Goldsmith-Pinkham et al., 2020). The second is a restriction on the interaction between the unobserved determinants U and the heterogeneity-invoking variable H. Specifically, the assumption implies that health shocks should not affect responsiveness to other macroeconomic time series.[20] Importantly, the assumptions allow for dependence between the variable of interest X and U, as well as for arbitrary interactions between X and U, and X and H. The sufficient overlap assumption (**A3.**) ensures that the conditional expectations in equation (5) are well-defined.

Several arguments are needed to justify unexpected changes in health and the associated response heterogeneity as plausibly exogenous. First, as described in Section III, we construct approximate measures of unexpected changes in health as the residuals of a first order vector autoregressive process. To address concerns regarding association between sudden changes in health and key household characteristics, we residualize explicitly with respect to age, education, race, wealth and income, and (for singles) gender. We further conduct our analysis stratifying by marital status. Note that this approach is a generalization of health shocks defined as in Wu (2003) and Berkowitz and Qiu (2006), who consider differences in severe health conditions.

Second, our analysis of older households addresses key concerns regarding response heterogeneity. While US households' health insurance and hence exposure to medical expenditure risk is often linked to employment, the health of older Americans is unlikely to affect their responsiveness to macroeconomic time series such as general economic uncertainty:

[20]For example, in order to disentangle households' response to the increase in health care policy uncertainty in 2017 from their response to the increase in trade policy uncertainty during the same time, the assumption imposes that deviations from expected health do not affect how households respond to trade policy uncertainty.

With the majority of the sample in retirement, most households we analyze are not at risk of greater exposure to medical expenditures due to potential job loss. Further, as illustrated by Smith (1999), labor supply will not be substantially altered by health shocks during retirement, and income from Social Security and pensions will remain fixed (i.e., not related to health).

B. Partial Identification of the ACE

Additional information on the value of particular conditional average causal effects can be leveraged in combination with the idenfified differences in conditional causal effects to derive a bound on the average (unconditional) causal effect. In our application, this information is derived from economic theory on background risk, which implies that risk averse households will decrease their relative demand for risky assets when faced with an undiversifiable risk such as increased health care policy uncertainty (Pratt and Zeckhauser, 1987; Kimball, 1993; Gollier and Pratt, 1996). Under the assumption that households are risk averse, this implies, in particular, that the conditional average causal effects of health care policy uncertainty on relative demand for risky assets are bounded above by zero:

$$\text{CACE}(x', x, h) \leq 0, \qquad \forall x' \geq x, h \in \mathcal{H}, \tag{6}$$

that is, households will not, on average, increase their demand for risky assets when health care policy uncertainty increases. An equivalent argument implies that the conditional average causal effects of health care policy uncertainty on the relative demand for safe assets are bounded below by zero.

Let $\bar{h}$ denote the value of the conditioning variable H for which the corresponding conditional average causal effect is the highest – that is, $\bar{h} \equiv \arg\max_{h \in \mathcal{H}} \text{CACE}(x', x, h)$.[21] Under inequality (6) and in combination with assumptions (**A1.**)- (**A3.**) of the previous subsection,

[21]Note that we may equivalently define $\bar{h} \equiv \arg\max_{h' \in \mathcal{H}} \text{DACE}(x', x, h', h)$ for an arbitrarily chosen $h \in \mathcal{H}$. Identification of $\bar{h}$ then follows from identification of the DACE.

it can be shown that

$$\begin{aligned}\text{ACE}(x', x) &= E\left[\text{DACE}(x', x, H, \bar{h})\right] + \text{CACE}(x', x, \bar{h}) \\ &\leq E\left[\text{DACE}(x', x, H, \bar{h})\right],\end{aligned} \tag{7}$$

where the integrated DACE, $E\left[\text{DACE}(x', x, H, \bar{h})\right]$, is a unique function of the data and can thus be estimated. See Supplemental Online Appendix C for the derivations.

We have thus translated the bound on the conditional average causal effect into a bound on the (unconditional) average causal effect of health care policy uncertainty, providing a novel causal identification approach in the macroeconomic context that does not rely on (conditional) independence of the variable of interest. Instead, the approach leverages an exogenous variable that potentially shifts responsiveness to the macroeconomic time series of interest but is assumed not to shift responsiveness to other macroeconomic variables.

Note that a bound on the (unconditional) average causal effect can be deduced directly from the assumption of risk averse agents – i.e., $\text{ACE}(x', x) \leq 0, \forall x' \geq x$ – even without our approach. However, this direct bound does not leverage any information in the data and would thus not allow for deeper quantitative insights regarding the magnitude of the effect of health care policy uncertainty. In many cases, therefore, it may be only marginally preferable to the most trivial of bounds (i.e., a bound from negative to positive infinity). The difference between the bound provided in (7) to this zero-upper (lower) bound depends crucially on the relevance of H: Although the assumptions for point identification of the DACE do not require that the variable H affects the responsiveness of households to the variable of interest X, the DACE that corresponds to an H that does not affect households' responsiveness is zero for all values of X; as a consequence, the bound of the ACE in this case is also zero. The greater the heterogeneity in responses induced by H to X, the more informative the bound on the average causal effect provided above. For practical usefulness, the choice of a relevant H is therefore important.

V. Estimation

Existing literature primarily conducts analyses of the effects of policy uncertainty within linear regression frameworks where the marginal effects of policy uncertainty are kept constant. These constant marginal effects have several advantages, including ease of estimation and communication of the empirical results. To facilitate comparisons of our results with previous analyses of policy uncertainty, we adopt the same approach and restrict the effect of health care policy uncertainty to be linear.[22] We emphasize, however, that our identification results are general enough that they can be used in analysis of nonlinear effects of policy uncertainty as well.

Estimation can be further simplified by using a linear multiplicative interaction specification for the heterogeneous effects of health care policy uncertainty conditional on the unexpected changes in health H. This simplification is equivalent to a functional form assumption for the structural function g in the regression given by

$$g(X, H, U) = \beta_0 + \beta_1(X \times H) + \beta_2 X + \beta_3 H + U, \tag{8}$$

where U is drawn from a mean-zero distribution with finite variance. Equation (8) corresponds to the multiplicative interaction framework typically considered in analyses of heterogeneous effects of policy uncertainty (e.g., Baker et al., 2016). Under standard regularity assumptions, the parameters in equation (8) may be estimated directly using ordinary least squares. In this framework, an estimate of the DACE for a unit change in X and a unit change in H is simply β_1. As illustrated in Section II, however, economic theory suggests substantial nonlinearities in the effects of health shocks. A first order approximation (as provided by the fully parametric approach in (8)) is therefore unlikely to capture key characteristics of the conditional distribution of the relative causal effects of health care policy uncertainty. An in-depth analysis requires a more flexible approach than the multiplicative interaction regression model.

[22]The restriction to linear effects of HCPU has the additional advantage of reducing the dimensionality of the conditional average causal effects such that effects conditional on a single health variable can be visualized with a line plot and effects conditional on two health variables can be visualized with a heatmap.

The presence of substantial nonlinearities in how health affects households' response to health care policy uncertainty motivates a semiparametric approach, where the marginal effect of health care policy uncertainty is kept constant for a fixed H, but may vary in an unspecified manner with different H. As a relaxation of the functional form assumption in equation (8), we therefore consider a model of the form

$$g(X, H, U) = \gamma_0(H) + \gamma_X(H) \times X + U, \tag{9}$$

where $\gamma_X : \mathcal{H} \to \mathbb{R}$, and U as before.[23] In this setting, the DACE for a unit change in X is given by the difference $\gamma_X(h') - \gamma_X(h)$ for two different values $h', h \in \mathcal{H}$. This semiparametric approach addresses the key concerns about prior restrictions on the influence of health by flexibly modelling the influence of health on the effect of health care policy uncertainty, while allowing for both easy interpretation within the broader literature on the effects of policy uncertainty and computational tractability through keeping the conditional marginal effects constant in X.

As discussed in the previous subsection, a choice of H that captures more of the heterogeneity of households' response to health care policy uncertainty will result in a strictly more informative bound on the average causal effect. This observation motivates using the complete set of five distinct health categories (introduced in Section III) when estimating the DACE as a first stage parameter in the construction of the ACE bound. Unfortunately, visualization of the DACE conditional on five variables is difficult. For illustrative purposes regarding the relative distribution of the conditional causal effect of health care policy uncertainty, we therefore also consider conditioning on a single health category (resulting in a single-dimensional DACE visualized by a line-plot) and two health categories (resulting in a two-dimensional DACE visualized by a heatmap).

When conditioning on a single health category, estimation of the semiparametric model defined by equation (9) is conducted using local linear regression. As traditional conventional

[23]Note that one may reparameterize $\gamma_X(H) \equiv \tilde{\gamma}_1 + \tilde{\gamma}_X(H)$ so that instead $\tilde{\gamma}_X$ measures deviations from the linear regression slope. This reparameterization highlights that equation (9) nests the multiplicative interaction specification of equation (8) as a special case.

semiparametric estimators suffer severely under the curse of dimensionality when conditioning on multiple variables, we apply the generalized random forests of Athey et al. (2019) when conditioning on more than one health category. The procedure allows for flexible interaction between types of health shocks; such flexible interaction is *a priori* likely to be a key feature of the DACE, while alleviating the curse of dimensionality through the inherent regularization of random forests.[24] We implement the generalized random forest estimator of the DACE with the R package provided by Tibshirani et al. (2020).

Once estimates of the DACE are obtained, the bound on the average causal effect of health care policy uncertainty can be constructed by the sample analogue of equation (7). In implementation, we take a slightly weaker approach than the one discussed in Section IV. Instead of bounding *all* conditional average causal effects by zero, a single value of H is chosen for which the corresponding effect is bounded by zero. Letting $h^\star$ denote this value for which we bound the conditional causal effect $\text{CACE}(x', x, h^\star)$, the bound on the average causal effect $\text{ACE}(x', x)$ is estimated via

$$\widehat{\text{ACE}}_{bound}(x', x) = \left(\hat{\gamma}_X(h^*) + \sum_{i=1}^{n} \hat{\gamma}_X(h_i) \right) \times (x' - x), \tag{10}$$

where $\hat{\gamma}_X$ denotes an estimate of γ_X obtained previously, and h_i is the value of the unexpected change in health for the ith observation in the sample of size n. This approach reduces the magnitude of the bound – because $\hat{\gamma}_X(h^*) \leq \max_{h \in \mathcal{H}} \hat{\gamma}_X(h)$ – but allows for more straightforward inference. The presented bounds should therefore be interpreted as being conservative.

Supplemental Online Appendix D provides pseudocode and further details on the implementation of our estimation and inference procedures.

[24] An earlier version of this paper considered a latent class model as well as the model-based recursive partitioning procedure by Zeileis et al. (2008) for the semiparametric estimation. Qualitative conclusions are not affected by the choice of these methods; however, the generalized random forests are computationally advantageous and allow for straightforward statistical inference. See Wiemann and Lumsdaine (2019) for further details.

VI. Results

This section presents the empirical results. First, the first-stage estimates of the difference in conditional average causal effects of health care policy uncertainty on households' portfolio choices are given using one and two health categories, respectively. These results provide insights into the distribution of the relative conditional effects but do not allow for inference on the absolute effects of health care policy uncertainty. Second, we provide bounds on the average causal effect of health care policy uncertainty based on the first-stage estimates using all five health categories simultaneously.

A. Estimates of the Difference in Conditional Average Causal Effects

Figure 2 presents estimates of the difference in conditional average causal effects based on unexpected changes to severe conditions (top panels) and on unexpected changes to nights spent in hospital (bottom panels).[25] The figures are normalized such that all estimates are relative to the conditional average causal effect of households that are substantially healthier than expected, which we define as having a more favorable unexpected change in the respective health category than 95% of households in the sample.[26] Note that because larger values for the health categories indicate worse health, negative values correspond to more favorable health. The horizontal axes are normalized to standard deviation units of the corresponding health category for ease of interpretation. The vertical axis shows percentage point differences in the dependent variable given a 100% increase in health care policy uncertainty – i.e., the figure plots the estimated values of the coefficients themselves (solid lines), denoted as $\gamma_X(H)$ in equation (9), where H are the constructed health measures, X is the log of the 12-month HCPU average, and Y is the relative share of risky (or safe) assets. For illustrative purposes, however, it is more interesting to consider the approximately 70% increase in the index, from the 2016 average of 110 to the 2017 average of 191 (see

[25] In the interest of space, estimates for only two of the health categories are presented here. Supplemental Online Appendix E provides analogous figures for the other health categories we consider.

[26] This baseline is chosen for interpretative reasons only and is akin to the choice of baseline in a linear regression that includes a constant and indicators of categorical variables with one (baseline) category suppressed.

also Figure 1). The latter year is associated with the extensive political efforts to repeal the Affordable Care Act. The dashed lines indicate bootstrapped 99% uniform confidence bands.[27]

[Figure 2 about here.]

The estimates indicate substantial heterogeneity in the effect of health care policy uncertainty with respect to unexpected changes in households' severe conditions and nights spent in hospital. Consider a single household with no unexpected changes to severe health conditions. Compared to a single household that finds itself with substantially fewer severe health conditions than expected, the first household increases its safe asset share by approximately 3.1 percentage points more, on average, when health care policy uncertainty increases by 70%. For couple households, the analogous increase in relative demand for safe assets amounts to 3.3 percentage points.[28] Similarly, when health care policy uncertainty increases by 70%, a single (couple) household with no unexpected changes to severe conditions decreases its risky asset share by approximately 2.2 (2.9) percentage points more than an analogous household with substantially fewer severe health conditions. That the increase in safe asset share is only partially offset by the decrease in risky asset share suggests that households increase their safe asset share not only by decreasing relative investment in stocks, but also by decreasing relative investment in the two excluded financial asset categories – bonds and IRA retirement accounts.

When considering instead unexpected changes in nights spent in hospital, the effects are a little less pronounced. A single (couple) household with no unexpected changes to nights spent in hospital increases its safe asset share by approximately 2.1 (1.6) percentage points

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[27]We implement the uniform confidence bands discussed in Montiel Olea and Plagborg-Møller (2019) using a grid of 100 evenly spaced samples from the horizontal axis as an approximation to the infinite-dimensional DACE. The bootstrap samples households rather than individual observations. This block bootstrap procedure thus accounts for dependence within households over time.

[28]The values are calculated by multiplying the height of the solid DACE curves in the top-left panel of Figure 2 at the origin of the horizontal axis (i.e., when $h = 0$) by 0.7.

when health care policy uncertainty increases by 70%, relative to a household with substantially fewer-than-expected nights in hospital. The analogous effects on relative demand for risky assets are 0.8 and 0.7 percentage points for single and couple households, respectively.

In addition to documenting heterogeneity in the effect of health care policy uncertainty with respect to unexpected changes in health, Figure 2 also suggests nonlinearities. In particular, households that are at their expected health level are estimated to react more strongly to increases in health care policy uncertainty than households that are in either substantially better or worse health than expected. These estimates are in line with economic theory on opposing mechanisms on the effect of health, as discussed in Section II. Interpreting the results in this fashion indicates that the background risk mechanism induced by higher expected health care costs drives the differences between households that are in better health than expected and those that are at their expected health. Differences between households that are in worse health than expected and households that are at their expected health, on the other hand, may be attenuated by the reduction in life expectancy and utility derived from consumption (see., e.g., Smith, 1999). Note that the uniform confidence bands in Figure 2 cannot reject linearity of the normalized DACE on a 99% confidence level.[29] The point estimates are therefore only suggestive of a nonlinear tradeoff between the two health mechanisms.

The DACE results so far condition on a single health category, effectively integrating over all possible interaction effects that may capture additional heterogeneity in households' response to health care policy uncertainty. In an effort to analyze interactions in two dimensions, at least, Figures 3 and 4 provide a heatmap of the DACE conditional on both unexpected changes in severe conditions and nights in hospital for safe and risky asset share,

[29]The reported uniform confidence bands encompass the set of functional forms of the normalized DACE that cannot be rejected on a 99% confidence level. Whether this set contains a linear functional form can be conveniently checked by assessing whether it is possible to draw a straight line segment starting at the reference point (in our example, the left-most point in the figure) that stays everywhere inside of the confidence bands without intersecting the bands. Curved confidence bands that are sufficiently tight will reject linearity, but wide bands cannot regardless of curvature. For further details on inference with uniform confidence bands see, for example, Montiel Olea and Plagborg-Møller (2019).

respectively. Panels (B) and (E) in the figures provide point estimates for couple and single households of the DACE, respectively, with darker purple representing a more negative response and darker red a more positive one. Similar to before, the results are normalized such that all estimates are relative to the conditional average causal effect of households that are substantially healthier than expected, which we now define as having a more favorable unexpected change in each of the two health categories than 95% of households in the sample.[30] To provide guidance on the sampling uncertainty corresponding to these point estimates, the left-most panels ((A) and (D)) and the right-most panels ((C) and (F)) provide the lower and upper bands, respectively, of the bootstrapped 99% uniform confidence bands.

[Figure 3 about here.]

[Figure 4 about here.]

Focussing first on the results for relative demand in safe assets in Figure 3, we find that single (couple) households who have no unexpected changes in both severe conditions and nights in hospital increase their safe asset share by 3.9 (5.3) percentage points when faced with a 70% increase in health care policy uncertainty, compared to households who find themselves with substantially fewer severe conditions and substantially fewer nights in hospital.[31] Similarly, the results for relative demand in risky assets in Figure 4 show that single (couple) households who have no unexpected changes in both severe conditions and nights in hospital decrease their risky asset share by 6.0 (4.9) percentage points when faced with a 70% increase in health care policy uncertainty, when compared to households with substantially fewer severe conditions and substantially fewer nights in hospital than expected.

The results indicate the relevance of interactions across different health categories for explaining heterogeneity in the effect of health care policy uncertainty on households' portfolio choice in that the magnitude of the heterogeneous effect is much larger when these

[30]This point corresponds to the bottom-left cell in each of the heatmaps.

[31]The values are calculated by multiplying the value of the DACE in panels (B) and (E) of Figure 3 at the intersection of the origin of the vertical and horizontal axes (i.e., when unexpected changes to both severe conditions and nights in hospital are zero) by 0.7.

interactions are considered. This motivates using the full set of five health categories for estimation of the DACE as a first stage parameter for the construction of a bound for the average causal effect of health care policy uncertainty, to which we turn next.

B. Bounding the Average Causal Effect

Table 1 presents estimates of the bounds of the average causal effects of health care policy uncertainty on the relative demand for risky and safe assets, for couple and single households, respectively. The estimates are based on bounding the conditional average causal effect by zero for households that are substantially better off than expected, which we again define here as having a more favorable unexpected change in each of the five health categories than 95% of households in the sample. Note that this approach results in more conservative estimates than bounding *all* households' conditional average causal effects by zero, independent of their health outcomes, which is justified by the assumption of risk averse agents. Brackets provide bootstrapped one-sided 95% confidence intervals.

[Table 1 about here.]

Focussing first on the safe asset share results in columns (1) and (2), the estimates suggest that couple and single households increase their safe asset share by *at least* 3.5 $(= 0.051 * 70)$ and $2.7 (= 0.039 * 70)$ percentage points, respectively, when faced with a 70% increase in health care policy uncertainty. Further, columns (3) and (4) indicate that couple and single households decrease their risky asset share by *at least* 1.5 and 2.3 percentage points, respectively, when faced with a 70% increase in health care policy uncertainty. With the exception of the bound for couple households on relative demand for risky assets, the estimates are significant on a 5% confidence level. Taken together, these results suggest that an increase in health care policy uncertainty shifts households' portfolio choice towards safe assets in the population, and – at least for single households – away from risky assets.

This inference comports with results from earlier studies. Also analyzing HRS data, Rosen and Wu (2004), Edwards (2008), and Love and Smith (2010), for example, respectively find that rating health in the worst category of the subjective health measure is associated with a 1%, 7%, and 1.8% decrease in the risky asset share. Our results thus show that a 70% increase in health care policy uncertainty, as has occurred between 2016 and 2017, shifts the relative demand for risky assets by at least as much as a considerable reduction in households' health, highlighting the importance of health care policy uncertainty as a determinant of households' relative demand for risky assets.

VII. Conclusion

In this paper, we develop a causal identification approach in the setting of a macroeconomic variable and its effect on microeconomic outcomes and apply it to study the effect of health care policy uncertainty on households' portfolio choice. Using semiparametric estimation, we find substantial nonlinear heterogeneity in the causal effect of health care policy uncertainty on households' safe and risky asset share with respect to unexpected changes in health. The estimates further suggest that health care policy uncertainty has statistically and economically significant effects on households' financial behavior in the population of older US households.

The empirical evidence suggests that an uncertainty increase similar to that associated with efforts to repeal the Affordable Care Act in 2017 decreases the relative demand for stocks and mutual funds by as much as a considerable reduction in health (e.g., Rosen and Wu, 2004). Given the large share of financial assets that older American couples in the HRS data have, the reduction in stock market participation may have direct implications for stock market volatility and the equity premium. Further, health care policy uncertainty appears to disproportionally affect households with unexpected adverse changes to health, which may exacerbate the socio-economic disadvantage associated with bad health in the US (Smith, 1999).

The recent COVID-19 pandemic has resulted in an unprecedented increase in economic and health care policy uncertainty (Altig et al., 2020). As countries begin to emerge from the COVID-19 pandemic, policymakers have sought to develop policies aimed at stimulating the economy, even as they continue to introduce measures to curtail the virus. These dual policy objectives also create a great deal of uncertainty for households. As health care policy likely remains at the center of political debates in the United States and elsewhere for the foreseeable future, further research into the macroeconomic implications of these policy discussions is necessary to assess potentially unintended consequences of political discourse. Our paper provides a flexible approach for analyzing such implications.

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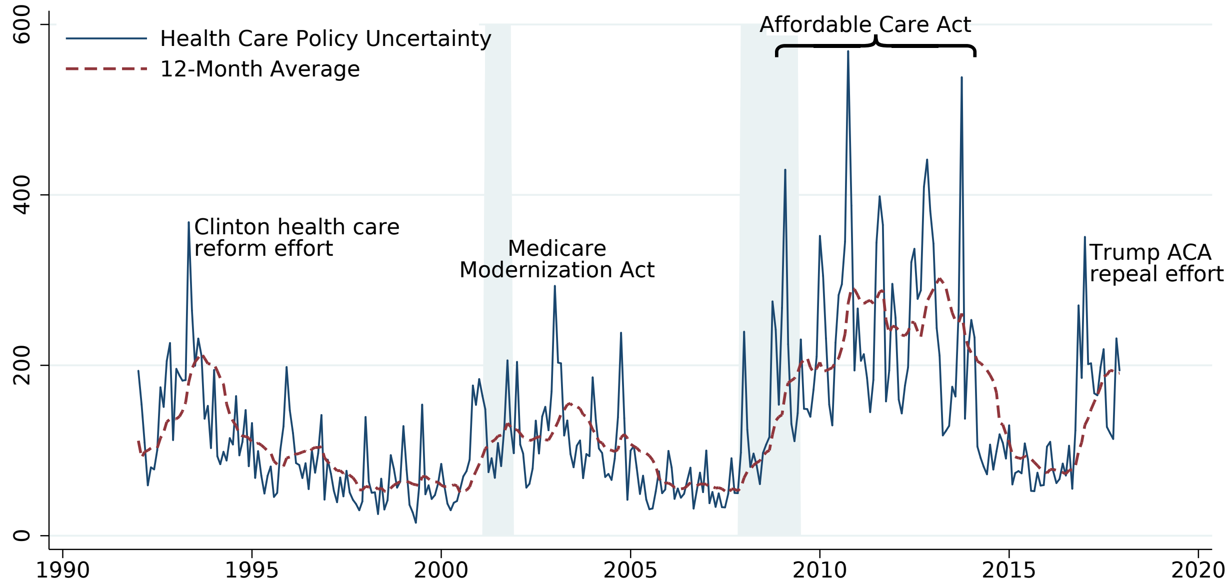
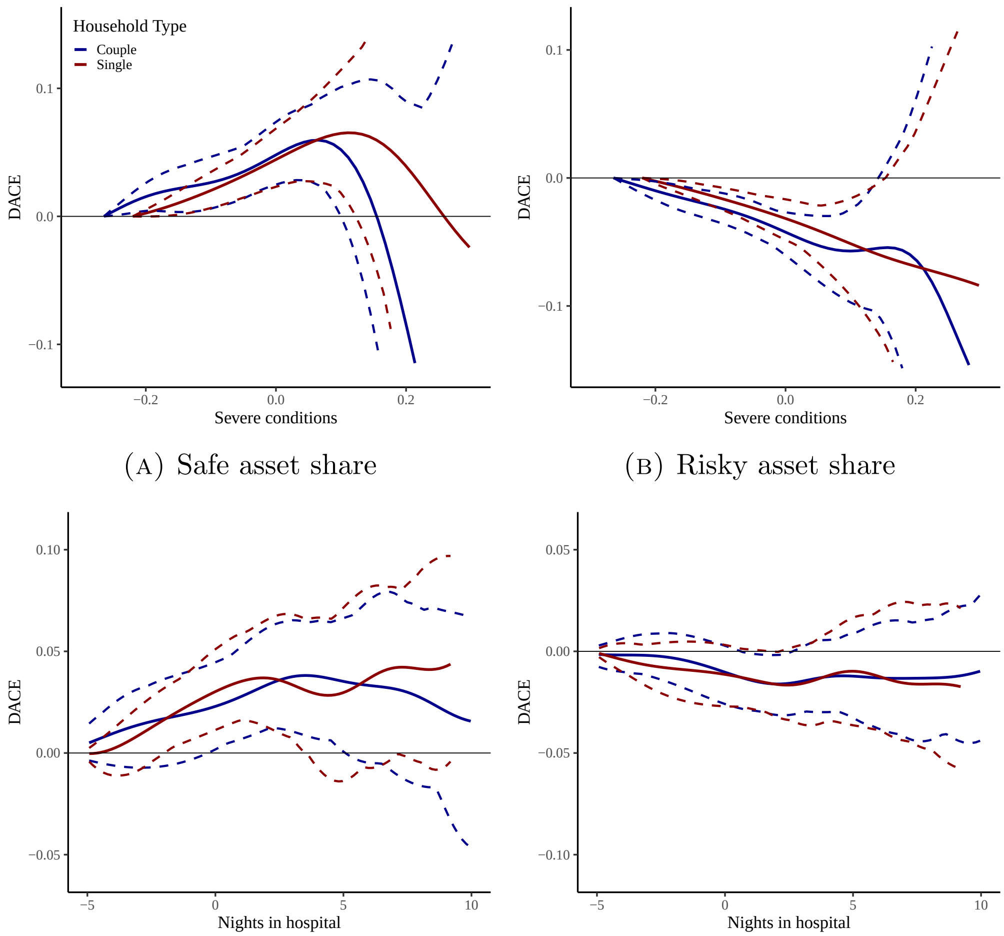
Figure 1
Health Care Policy Uncertainty Index 1992 – 2017



Notes. The Baker et al. (2016) index plotted in this figure reflects the scaled monthly number of newspaper articles containing the word-triplet "uncertain", "economic", and "policy" (and their synonyms) and one term on health care (e.g., "health insurance"). It is calculated on basis of the Access World News newspaper archive with about 1,500 US papers, normalized to a mean of 100 from 1985 to 2010. The dashed line is the index's average based on the preceding 12 months. The shaded areas represent NBER recession periods. Baker et al. (2016) provide a similar figure of the health care policy uncertainty index until January 2015. We update the authors' figure through December 2017, adding also the series' 12-month average and NBER recession bars.

FIGURE 2

Normalized DACE Estimates for Couple and Single Households



(A) Safe asset share

(B) Risky asset share

(C) Safe asset share

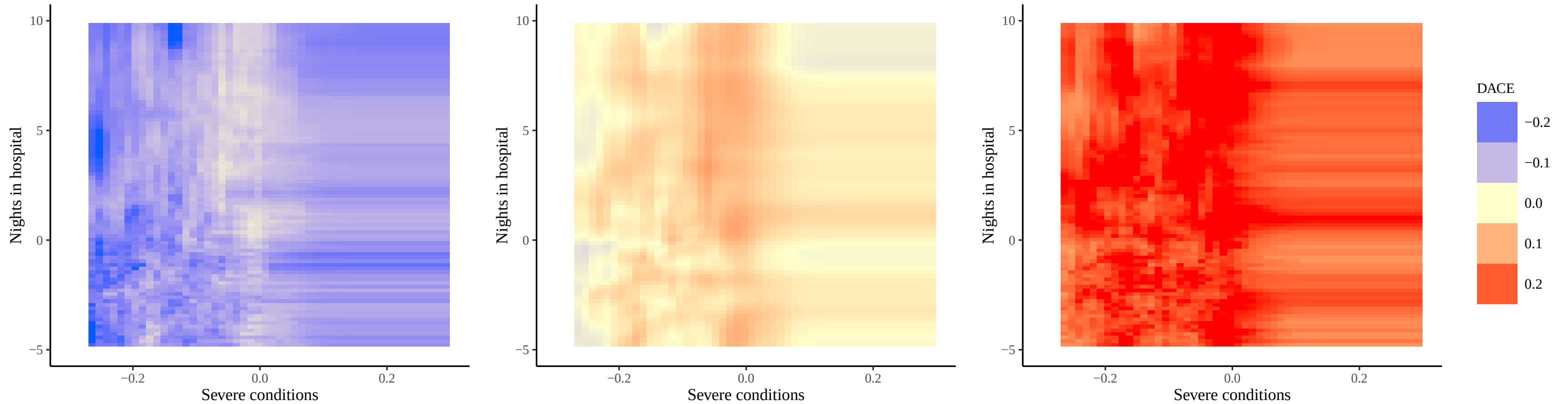
(D) Risky asset share

Notes. These figures show the local linear regression-based estimates of differences in average causal effects (DACE) of health care policy uncertainty on safe and risky asset share, respectively, conditional on a single health category, for two specific examples: severe conditions (figures A and B) and nights in hospital (figures C and D). The estimates presented are relative to the baseline of households that are in substantially better health than expected, defined here as having a more favorable unexpected change in the corresponding health category than 95% of households in the sample. The plots are based on $B = 1,000$ bootstrap draws, where the solid lines correspond to the mean and the dashed lines correspond to bootstrapped 99% confidence bands. Blue lines correspond to couple households and red lines correspond to single households.

FIGURE 3

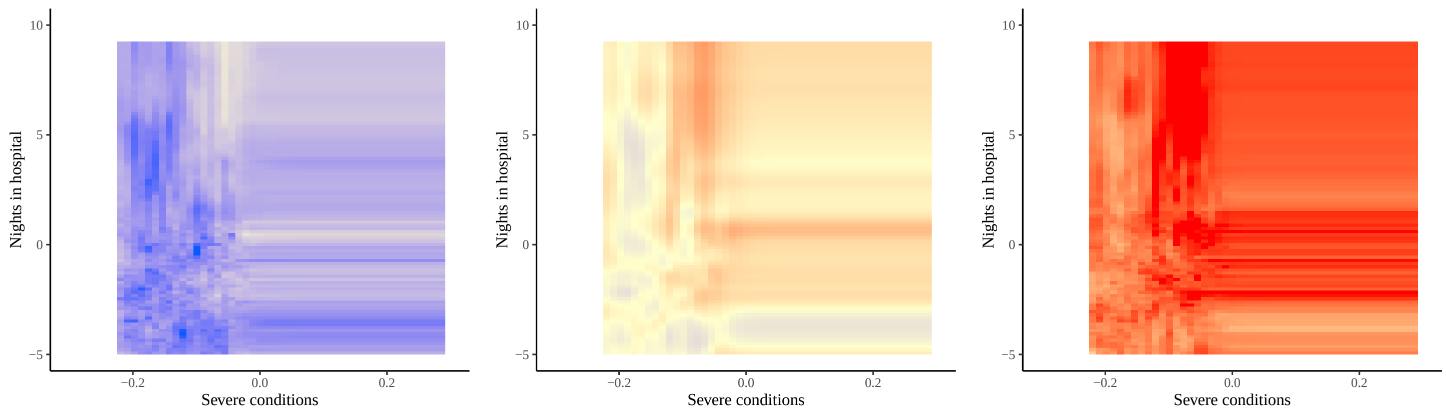
Normalized DACE on Safe Asset Share using two Health Categories

Panel 1: Couple Households



(A) Lower confidence band (B) Mean (C) Upper confidence band

Panel 2: Single Households



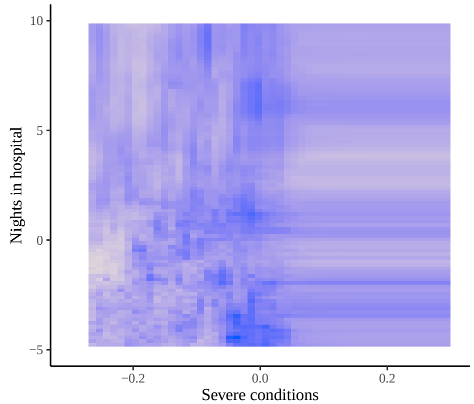
(D) Lower confidence band (E) Mean (F) Upper confidence band

Notes. These figures show the random forest-based estimates of the differences in average causal effects (DACE) of health care policy uncertainty on the *safe asset share* conditional on two health categories (severe conditions and nights in hospital). The estimates are relative to the baseline of households that are in substantially better health than expected, defined here as having a more favorable unexpected change in each of the corresponding health categories than 95% of households in the sample. Plots are based on $B = 1,000$ bootstrap draws, where the center panels ((B) and (E)) correspond to the mean, while the left-most panels ((A) and (D)) and the right-most panels ((C) and (F)) provide the bootstrapped lower and upper 99% uniform confidence bands, respectively.

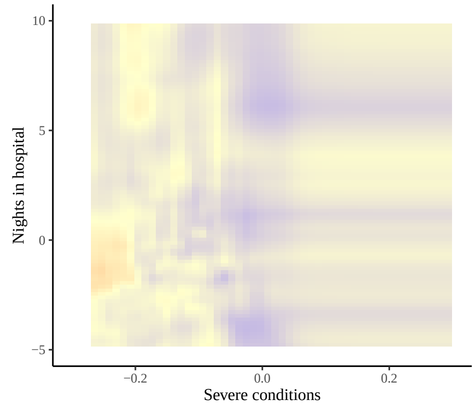
FIGURE 4

Normalized DACE on Risky Asset Share using two Health Categories

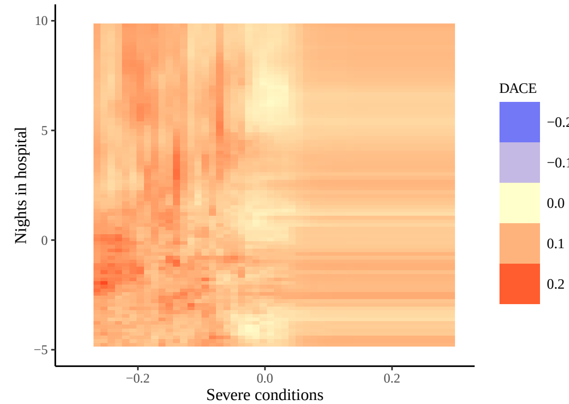
Panel 1: Couple Households



(A) Lower confidence band

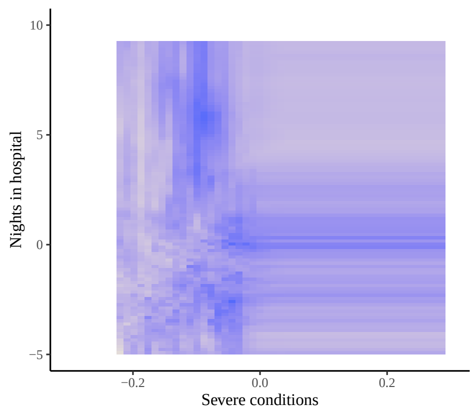


(B) Mean

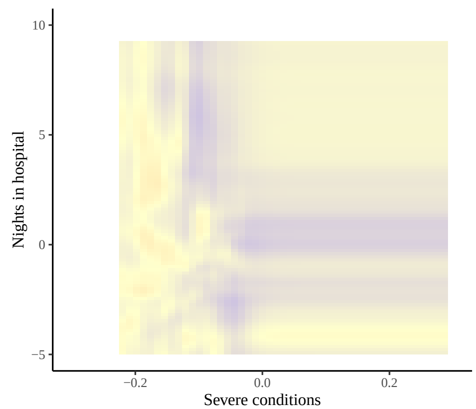


(C) Upper confidence band

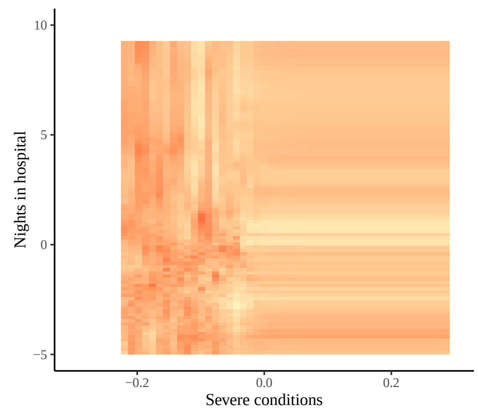
Panel 2: Single Households



(D) Lower confidence band



(E) Mean



(F) Upper confidence band

Notes. These figures show the random forest-based estimates of the differences in average causal effects (DACE) of health care policy uncertainty on the *risky asset share* conditional on two health categories (severe conditions and nights in hospital). See notes to Figure 3 (the construction and interpretation of these figures is similar and in the interest of space those details are not repeated here).

TABLE 1

Bounds on the Average Causal Effect

Safe Asset Share		Risky Asset Share	
Couples	Singles	Couples	Singles
(1)	(2)	(3)	(4)
0.051	0.039	-0.022	-0.033
$[0.015, \infty)$	$[0.012, \infty)$	$(-\infty, 0.005]$	$(-\infty, -0.013]$

Notes. The table presents estimates of the bound on the average causal effect of health care policy uncertainty, $E\left[\text{DACE}(x', x, H, \bar{h})\right]$,where $\bar{h}$ is defined here as having a more favorable unexpected change in each of the five health categories than 95% of households in the sample. Brackets contain one-sided confidence intervals covering of 95% of bootstrapped bounds

Effects of Health Care Policy Uncertainty on Households' Portfolio Choice

Supplemental Appendices (for online publication only)

Thomas T. Wiemann and Robin L. Lumsdaine

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Appendices

A. Dataset Citations

The following provides references to the data sources compiled for the analysis in the main text and the appendix.

Baker, Scott R, Bloom, Nicholas, and Davis, Steven J (2020). Categorical EPU Data. Retrieved on January, 2020, from `https://www.policyuncertainty.com/categorical_epu.html`.

Health and Retirement Study (2018). RAND HRS CAMS Spending Data 2015 (V2) public use dataset. Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

Health and Retirement Study (2018). RAND HRS Longitudinal File 2014 (V2) public use dataset. Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

United States Bureau of Labor Statistics (2018). Consumer Price Index for All Urban Consumers: All Items. Retrieved on June 20, 2018, from `https://beta:bls:gov/dataViewer/view/timeseries/CUSR0000SA0`.

B. Construction of the Analysis Sample

Starting with the initial HRS sample of 68,507 single and 72,426 couple households that have a non-zero household sampling weight, we exclude 16,084 and 8,702 observations, respectively, that have no positive holdings of financial assets.[1] An additional 3,707 and 4,095 single and couple household observations, respectively, are omitted from the analysis due to missing one or more of the variables used in estimation. Finally, households with an observation in only one wave (3,332 and 2,439 observations for single and couple households, respectively) are excluded to ensure that the samples will be identical across the fixed effect and pooled models. This leaves a sample of 45,384 single and 57,190 couple household-wave observations for the portfolio choice analysis.

Table B.1 shows the number of observations that were excluded from the analysis sample due to missing information. The first two columns ("HRS") describe the data used in the main analysis while the third and forth columns ("CAMS") describe the Consumption and Activities Mail Survey data used in the supplemental analysis of consumption in Appendix G. The difference in starting observations for each subsample is due to unequal distribution of couple and single households.

The reductions in sample size are in line with existing studies that use the HRS dataset for household analysis. In particular, Love and Smith (2010) consider the first nine waves of the HRS (1992-2006) with a total sample size of 37,962 and 43,595 for single and couple households, respectively. In comparison with the eleven HRS waves (1994-2014) employed in this paper, these numbers point to a similar proportion of observations excluded. Most recently, Gábor-Tóth and Georgarakos (2019) consider the CAMS dataset also employed in this study. The authors consider a pooled single and couple households sample of 19,797 observations for their analysis, similar to the sample we use (with a total of 20,752 observations used for analysis of consumption).

[1] In doing so, we follow Rosen and Wu (2004) who also consider households conditional on holding positive financial assets.

Table B.1
Tabulation of Deleted Observations

		HRS		CAMS	
		Single	Couple	Single	Couple
Starting		68,507	72,426	17,847	11,811
Risky asset share	-	16,084	8,702		
Consumption	-			4,022	2,837
Education	-	7	6	0	0
Race	-	12	1,393	11	298
Self-reported health	-	46	34	12	6
Severe conditions	-	281	199	66	31
Mobility	-	2,916	2,223	55	14
ADLs	-	1	5	0	0
Hospital nights	-	444	235	73	34
Households recorded in only one wave	-	3,332	2,439	972	475
Final # of observations	=	45,384	57,190	12,636	8,116
Final # of unique households		10,022	10,555	2,983	1,765

Notes. The table provides the number of observations sequentially deleted from the sample due to missing observations in each variable. Additionally, households that are recorded in only one wave or have no total spending are excluded from the analysis. The two bottom rows show the number of final observations and the associated number of unique households, respectively.

Table B.2 presents complementary summary statistics. Nominal financial values are converted to 2010 US dollars using the Consumer Price Index corresponding to the 12 months preceding the respective interview's end-date. Single households are disproportionately female (more than 71%) and despite being nearly five years older on average, are healthier both in terms of self-reported health and most other indicators (all except ADLs). Couple households tend to have a greater share of risky assets (and a lower share of safe assets), consistent with theories of risk-sharing and diversification.

TABLE B.2
Summary Statistics

Single households	Mean	Sd.		Mean	Sd.		Share
Asset Shares			*Hh Characteristics*			*Hh Proportions (%)*	
Risky assets	0.136	0.278	Self-reported health	2.839	1.101	Female	0.713
Safe assets	0.679	0.399	Severe conditions	0.717	0.905	Retired	0.575
IRA	0.171	0.308	Mobility	1.750	1.822	No high school	0.176
Bonds	0.015	0.085	ADLs	0.465	1.169	GED	0.038
Macro. Variables			Hospital nights	2.344	9.130	High school	0.329
HCPU	127.421	102.519	Income ($100,000)	0.437	1.101	Some college	0.247
HCPU_{12}	131.353	75.675	Wealth ($100,000)	2.974	11.692	Above college	0.209
			Years ret.	8.288	10.885	White	0.863
			Age	69.113	11.296	Black	0.100
						Other	0.037

Couple households	Mean	Sd.		Mean	Sd.		Share
Asset Shares			*Hh Characteristics*			*Hh Proportions (%)*	
Risky assets	0.167	0.284	Self-reported health	3.058	1.017	Retired	0.579
Safe assets	0.517	0.409	Severe conditions	0.895	0.908	No high school	0.047
IRA	0.299	0.360	Mobility	1.883	1.747	GED	0.023
Bonds	0.016	0.080	ADLs	0.469	1.199	High school	0.243
Macro. Variables			Hospital nights	2.892	10.929	Some college	0.273
HCPU	128.632	102.413	Income ($100,000)	1.056	2.378	Above college	0.414
HCPU_{12}	133.243	74.815	Wealth ($100,000)	5.408	13.573	White-White	0.886
			Years ret.	6.887	9.188	Black-Black	0.048
			Age	64.943	9.280	Other-Other	0.020
						White-Black	0.005
						White-Other	0.039
						Black-Other	0.003

Notes. Statistics for single households are based on the sample of 45,384 household-wave observations. For couple households, there are 57,190 observations used in the analysis. The HRS-provided household analysis weights are used for calculation. Following Rosen and Wu (2004), safe assets are checking and savings accounts, CDs, government savings bonds and T-bills, and risky assets are stocks and mutual funds. HCPU_{12} denotes the 12-month average of Baker et al.'s (2016) health care policy uncertainty. Health measures, age, years of retirement, retirement status, and highest obtained education are defined as the maximum across spouses. $ denotes 2010 Dollars.

C. Identification Results

This appendix outlines the key identification results. After deriving point identification of the difference in conditional average causal effects (DACE) under suitable assumptions, we review conditions under which the average causal effect (ACE) is point or partially identified.

C.1. Point Identification of Differences in Conditional Causal Effects

Let $Y = g(X, H, U)$, with $Y \in \mathcal{Y}$, denote the latent variable model considered in Section IV, where $X \in \mathcal{X}$ and $H \in \mathcal{H}$ are observed determinants of Y, $U \in \mathcal{U}$ are unobserved determinants of Y, and $g : \mathcal{X} \times \mathcal{H} \times \mathcal{U} \to \mathcal{Y}$ is an unknown function.

Define the average causal effect (ACE) as

$$\text{ACE}(x', x) \quad \equiv \quad E\left[g(x', H, U) - g(x, H, U)\right], \tag{C.1}$$

where the expectation is over both the unobserved U as well as the observed H. Additionally, define the conditional average causal effect (CACE) as

$$\text{CACE}(x', x, h) \quad \equiv \quad E\left[g(x', h, U) - g(x, h, U)\right], \tag{C.2}$$

where the expectation is over U and H is fixed at the specific value $H = h$. The expected difference in the conditional average causal effect (DACE) under two hypothetical states of the variable H for an arbitrary individual in the population is then simply given by

$$\text{DACE}(x', x, h', h) \quad \equiv \quad \text{CACE}(x', x, h') - \text{CACE}(x', x, h). \tag{C.3}$$

Notice that the ACE, CACE, and DACE, as introduced in equations (C.1)-(C.3) are functions of expectations over the unobservables U and thus cannot be directly estimated using their sample analogues.

The assumptions necessary for nonparametric identification of the DACE differ from those of the ACE and CACE. In particular, we can provide a set of assumptions under which the DACE is identified even when the ACE and CACE are unidentified. In addition to the existence of appropriate moments, which is assumed throughout, a set of sufficient assumptions for the nonparametric identification of the DACE(x', x, h', h) is given by

A1. $H \perp\!\!\!\perp U$ (H-exogeneity),

A2. $\{g(x, h', U) - g(x, h, U)\}_{x\in\{x',x\},h,h'\in\{h',h\}} \perp\!\!\!\perp X$ (Exogenous response heterogeneity),

A3. $f_{XH}(\tilde{x}, \tilde{h}) > 0, \quad \forall \tilde{x} \in \{x', x\}$ and $\tilde{h} \in \{h', h\}$, where f_{XH} denotes the joint pdf or pmf (Sufficient overlap).

The first (H-exogeneity) and second (Exogenous response heterogeneity) assumptions state that the variable H is randomly assigned and does not shift responsiveness with respect to those unobservables U that are not independent of the variables of interest X. In the context of this paper, these assumptions imply that unexpected changes in health do not shift responsiveness with respect to any macroeconomic variables that are not independent of health care policy uncertainty.[2] The third assumption is a technical condition to ensure that the conditional expectations considered here are well-defined.

Suppose Assumptions 1-3 hold. Then

$$\begin{aligned}
\mathrm{DACE}(x', x, h', h) &= \mathrm{CACE}(x', x, h') - \mathrm{CACE}(x', x, h) \\
&= (E[(g(x', h', U) - g(x, h', U)) - (g(x', h, U) - g(x, h, U))]) \\
&= (E[(g(x', h', U) - g(x', h, U)) - (g(x, h', U) - g(x, h, U))]) \\
&= (E[g(x', h', U) - g(x', h, U)|X = x']) \\
&\qquad - (E[g(x, h', U) - g(x, h, U)|X = x]) \\
&= (E[g(x', h', U)|X = x'] - E[g(x, h', U)|X = x]) \\
&\qquad - (E[g(x', h, U)|X = x'] - E[g(x, h, U)|X = x]) \\
&= (E[Y|X = x', H = h'] - E[Y|X = x, H = h']) \\
&\qquad - (E[Y|X = x', H = h] - E[Y|X = x, H = h]),
\end{aligned} \tag{C.4}$$

[2]For example, unexpected changes in health may affect how households respond to health care policy uncertainty, but it does not affect how households respond to trade policy uncertainty.

which shows that the DACE may be expressed as a unique function of the observable data and is thus identified in the sense of Hurwicz (1950).

C.2. Identification of the Average Causal Effect

We now turn to identifying the average causal effect using the identified DACE from the previous subsection. For this purpose, we need not just access to a single DACE – that is, conditional on two specific values $H = h'$ and $H = h$ – but the entire relative distribution of conditional average causal effects: $\text{DACE}(x', x, h', h), \forall h, h' \in \mathcal{H}$. Assumptions 2 and 3 discussed in the previous section need to be reformulated to hold for all possible pairs of values of the conditioning variable H:

A2'. $\{g(x, h', U) - g(x, h, U)\}_{x \in \{x', x\}, h, h' \in \mathcal{H}} \perp\!\!\!\perp X$ (Exogenous response heterogeneity),

A3'. $f_{XH}(\tilde{x}, \tilde{h}) > 0, \quad \forall \tilde{x} \in \{x', x\}$ and $\tilde{h} \in \mathcal{H}$, where f_{XH} denotes the joint pdf or pmf (Sufficient overlap).

Note with these slightly stronger assumptions (compared to those of the previous section) the ensuing interpretation has not changed.

Define now a parameter for a specific conditional average causal effect, $\tau^\star := \text{CACE}(x', x, h^\star)$, where $h^\star$ is a particular value of H.[3] Then,

$$
\begin{aligned}
& \text{DACE}(x', x, h', h^\star) = \text{CACE}(x', x, h') - \text{CACE}(x', x, h^\star) \\
\Rightarrow \quad & \text{CACE}(x', x, h') = \text{DACE}(x', x, h', h^\star) + \tau^\star \\
\Rightarrow \quad & E\left[\text{CACE}(x', x, H)\right] = E\left[\text{DACE}(x', x, H, h^\star)\right] + \tau^\star \\
\Rightarrow \quad & \text{ACE}(x', x) = E\left[\text{DACE}(x', x, H, h^\star)\right] + \tau^\star,
\end{aligned}
\tag{C.5}
$$

where the last equation follows from the definitions of the ACE and CACE and the law of iterated expectations. Equation (C.5) shows that the average causal effect, $\text{ACE}(x', x)$, is identified up to the additive constant $\tau^\star$.

[3]Note that the notation $h^\star$ is meant to highlight consideration of a particular value of H, as distinct from an (unspecified) value in its support $h \in \mathcal{H}$.

The expression derived in equation (C.5) is of little interest unless information on $\tau^\star$ is available: a trivial bound on $\tau^\star$ would result in a trivial bound on $\text{ACE}(x', x)$. However, when additional information on $\tau^\star$ is available, the equation allows for straightforward translation from information about (a single) CACE to information about the ACE.

In this paper, we employ the additional assumption of risk averse agents to derive information about $\tau^\star$. In particular, the risk averse households assumption implies that the conditional average causal effect of health care policy uncertainty on relative demand for risky assets is bounded above by zero, that is,

$$\text{CACE}(x', x, h) \leq 0, \quad \forall x' \geq x, h \in \mathcal{H}. \tag{C.6}$$

Let $\bar{h}$ denote the maximum value of CACE across all households, that is, the value of H such that $\text{CACE}(x', x, \bar{h}) \geq \text{CACE}(x', x, h), \forall h \in \mathcal{H}$ and $x' \geq x$. Then equation (C.5) implies

$$\begin{aligned} \text{ACE}(x', x) &= E\left[\text{DACE}(x', x, H, \bar{h})\right] + \text{CACE}(x', x, \bar{h}) \\ &\leq E\left[\text{DACE}(x', x, H, \bar{h})\right], \end{aligned} \tag{C.7}$$

which shows that a bound on the average causal effect is partially identified in this setting.

Identification of the ACE in this fashion may incorporate information about CACE in a variety of forms. The example given here translated a non-trivial bound on the CACE into a non-trivial bound on the ACE. Similarly, equation (C.5) allows for translation of a point value on the CACE into a point value of the ACE, or mapping of a distribution of the CACE into a distribution of the ACE.

D. Implementation Details

This appendix provides pseudocode for the estimation procedures of the relative distributions of the differences in conditional average causal effects (e.g., Figure 2) and the bounds on the average causal effect (see Table 1).

Algorithm 1 provides the pseudocode that serves as a first-step basis for plotting the relative distribution of the differences in conditional average causal effects. Once the local linear regression coefficients – denoted here as $\hat{\gamma}_k^{(b,s)}$, where b denotes the bootstrap iteration, s corresponds to a particular value on the horizontal axis, and k denotes one of the health categories – are calculated, this relative distribution may readily be calculated. For a particular $k \in \{1, \dots, \dim H\}$ and a selected baseline $s^\star \in \{1, \dots, S\}$, we can calculate $\hat{\gamma}_k^{(b,s)} - \hat{\gamma}_k^{(b,s^\star)}$ for each $b \in \{1, \dots, B\}$. For each s, this allows for straightforward calculation of bootstrap statistics such as the mean or the 99% confidence bands using Algorithm 2 in Montiel Olea and Plagborg-Møller (2019).

Algorithm 1 BOOTSTRAPLLR

<u>Required input</u>: B number of bootstraps; $\{(y_{it}, \mathrm{HCPU}_t, H_{it}, X_{it})\}_{i\in\mathcal{D}, t\in\mathcal{T}}$ the data, where $\mathcal{D}$ is the set of households and $\mathcal{T}$ is the set of time periods; $\{h_k^{(s)}\}_{s\in\{1,\dots,S\}, k\in\{1,\dots,\dim H\}}$ a set of values for the H-variables for which to calculate the local linear regression coefficients;

procedure BOOTSTRAPLLR
- **for** $b \in \{1, \dots, B\}$ **do**
  - $\mathcal{D}_b \leftarrow \textsc{Sample}(\mathcal{D})$ ▷ Block-bootstrap households
  - $\{\tilde{H}_{it}^{(b)}\}_{i\in\mathcal{D}_b, t\in\mathcal{T}} \leftarrow \textsc{Residualize}(\{H_{it}, X_{it}\}_{i\in\mathcal{D}_b, t\in\mathcal{T}})$ ▷ Residualize H-variables
  - **for** $k \in \{1, \dots, \dim H\}$ **do**
    - **for** $s \in \{1, \dots, S\}$ **do**

$$\hat{\gamma}_k^{(b,s)} \leftarrow \arg\min_{\gamma} \min_{\alpha,\beta} \sum_{i\in\mathcal{D}_b, t\in\mathcal{T}} K\left(\tilde{H}_{it,k}^{(b)}, h_k^{(s)}\right)\left(y_{it} - \alpha - \tilde{h}_{it,k}^{(b)}\beta - \log \mathrm{HCPU}_t\gamma\right)^2 \tag{D.1}$$

<u>Return</u>: $\{\hat{\gamma}_k^{(b,s)}\}_{b\in\{1,\dots,B\}, s\in\{1,\dots,S\}, k\in\{1,\dots,\dim H\}}$

Notes. $\dim H$ denotes the dimension of the vector of H-variables, SAMPLE denotes the function that samples households from the empirical distribution of households with replacement. RESIDUALIZE denotes the VAR-based residualization procedure outlined in Section III. $K(\cdot,\cdot)$ denotes the Gaussian kernel function. The kernel bandwidths are chosen using the Silverman (1989) rule.

The heatmap figures for visualizing the relative distribution of the differences in conditional average causal effects (e.g., Figure 3) can be generated in similar fashion. This is done by replacing the local linear regression specification in equation (D.1) below with a generalized random forest of Athey et al. (2019). Note that instead of providing a sequence of values for each health category as in Algorithm 1, computation of the heatmaps with the generalized random forests requires providing a grid of values for each pair of health categories under consideration.

Algorithm 2 provides the pseudocode for estimation of the bounds on the average causal effects presented in Table 1. From the estimated average causal effects in each bootstrap iteration, we can calculate bootstrap statistics such as the mean or the 95th percentile of bootstrap draws.

Algorithm 2 BootstrapACE

Required input: B number of bootstraps; $\{(y_{it}, \mathrm{HCPU}_t, H_{it}, X_{it})\}_{i\in\mathcal{D},t\in\mathcal{T}}$ the data, where $\mathcal{D}$ is the set of households and $\mathcal{T}$ is the set of time periods; $H^\star$ a set of values for the H-variables that serve as a baseline case for which $\mathrm{CACE}(x', x, H^\star) \geq \mathrm{CACE}(x', x, h)$ or $\mathrm{CACE}(x', x, H^\star) \leq \mathrm{CACE}(x', x, h), \forall h \in \mathcal{H}$ is assumed;

procedure BootstrapACE

    for $b \in \{1, \ldots, B\}$ **do**

        $\mathcal{D}_b \leftarrow \textsc{Sample}(\mathcal{D})$ ▷ Block-bootstrap households

        $\{\tilde{H}_{it}^{(b)}\}_{i\in\mathcal{D}_b,t\in\mathcal{T}} \leftarrow \textsc{Residualize}(\{H_{it}, X_{it}\}_{i\in\mathcal{D}_b,t\in\mathcal{T}})$ ▷ Residualize H-variables

        $\hat{g}^{(b)} \leftarrow \textsc{CausalForest}(\{(y_{it}, \log \mathrm{HCPU}_t, \tilde{H}_{it}^{(b)})\}_{i\in\mathcal{D}_b,t\in\mathcal{T}})$

        $\{\hat{\gamma}_{it}^{(b)}\}_{i\in\mathcal{D}_b,t\in\mathcal{T}} \leftarrow \hat{g}^{(b)}(\tilde{H}_{it}^{(b)})$

        $\hat{\gamma}^{(b,\star)} \leftarrow \hat{g}^{(b)}(H^\star)$

        $\widehat{\mathrm{ACE}}^{(b)} \leftarrow \frac{1}{NT}\sum_i \sum_t \hat{\gamma}_{it}^{(b)} - \hat{\gamma}^{(b,\star)}$

Return: $\{\hat{\gamma}_k^{(b,s)}\}_{b\in\{1,\ldots,B\},s\in\{1,\ldots,S\},k\in\{1,\ldots,\dim H\}}$

Notes. Sample denotes the function that samples households from the empirical distribution of households with replacement. Residualize denotes the VAR-based residualization procedure outlined in Section III. CausalForest corresponds to the implementation provided by Tibshirani et al. (2020).

E. Additional Estimation Results

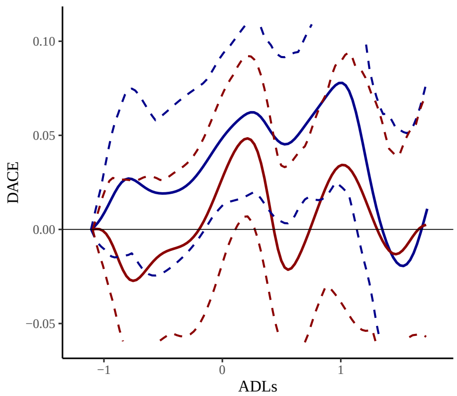
This appendix contains estimation results corresponding to the three other health categories considered in the paper: self-reported health, mobility, and ADLs. For all figures in this appendix, the estimates are relative to the baseline of households that are in substantially better health than expected, defined here as having a more favorable unexpected change in the corresponding health category than 95% of households in the sample. The plots are based on $B = 1,000$ bootstrap draws.

Figure E.1 shows the line plots that describe the relative distribution of conditional average causal effects using single health category. As with Figure 2 in the main text, these plots show the local linear regression-based estimates of differences in average causal effects of health care policy uncertainty on safe and risky asset share, respectively, conditional on a single health category. The solid lines correspond to the mean and the dashed lines correspond to the bootstrapped 99% uniform confidence bands, respectively. The figure shows the relative distribution conditional on ADLs (Figures (A) and (B)), mobility (Figures (C) and (D)), and self-reported health (Figures (E) and (F)).

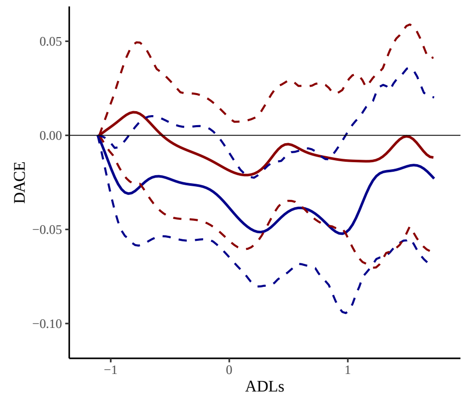
Additional heatmap figures describing the relative distribution of conditional average causal effects using two health categories are given in Figures E.2 to E.7. As with Figure 3 in the main text, the center panels correspond to the mean, while the left and the right-most panels provide the bootstrapped lower and upper 99% uniform confidence bands, respectively. Each page of figures presents estimates for couple households in the upper panel (Panel 1) and single households in the lower panel (Panel 2).

Figures E.2 and E.3 show the random forest-based estimates of differences in average causal effects of health care policy uncertainty on safe and risky asset share, respectively, conditional on severe conditions and ADLs. Figures E.4 and E.5 contain analogous plots conditional on severe conditions and mobility. Figures E.6 and E.7 contain the final pair of plots, conditional on severe conditions and self-reported health.

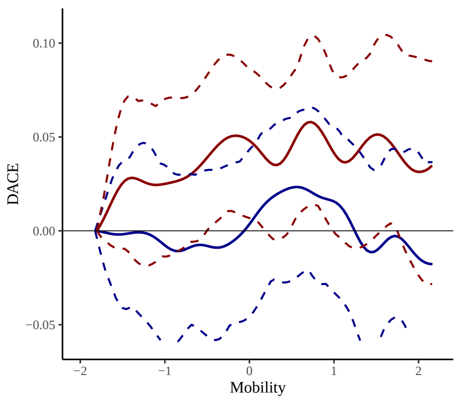
Figure E.1
Normalized DACE Estimates for Couple and Single Households (Additional Results)



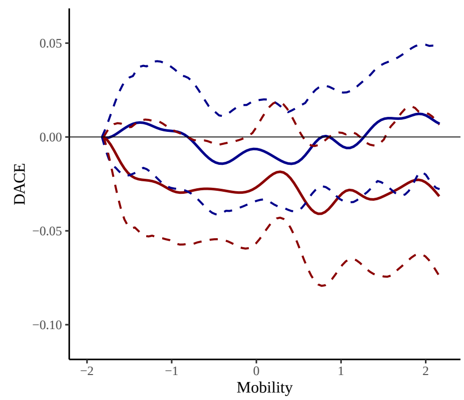
(a) Safe asset share



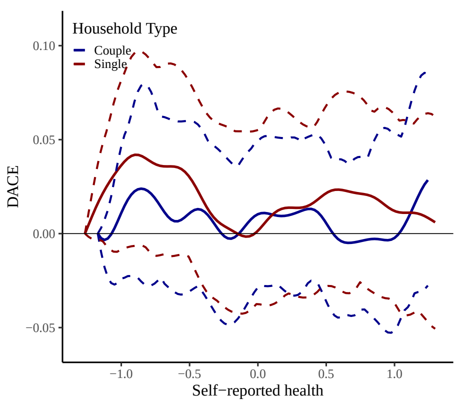
(b) Risky asset share



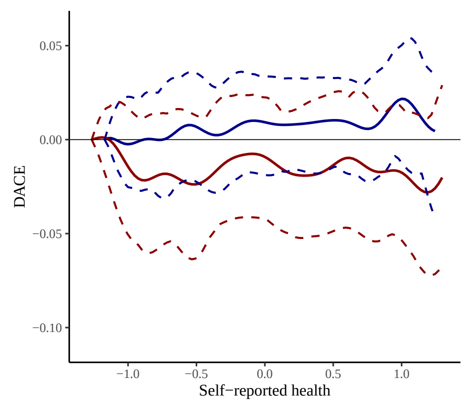
(c) Safe asset share



(d) Risky asset share



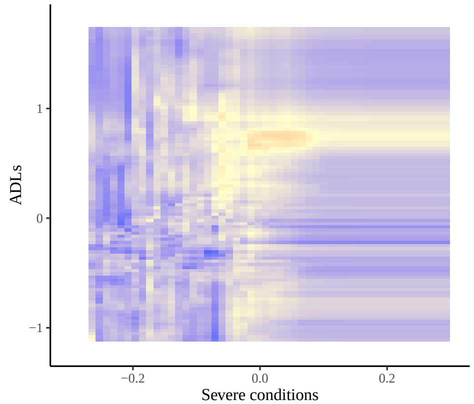
(e) Safe asset share



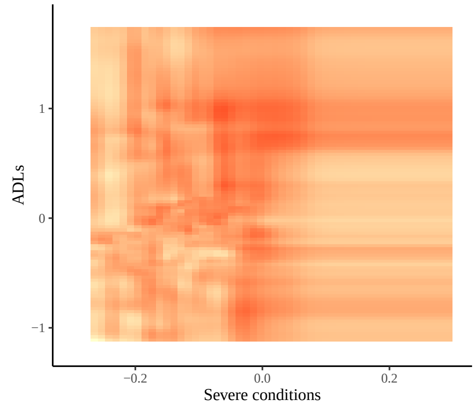
(f) Risky asset share

Figure E.2
Normalized DACE on Safe Asset Share using Severe Conditions and Activities of Daily Living

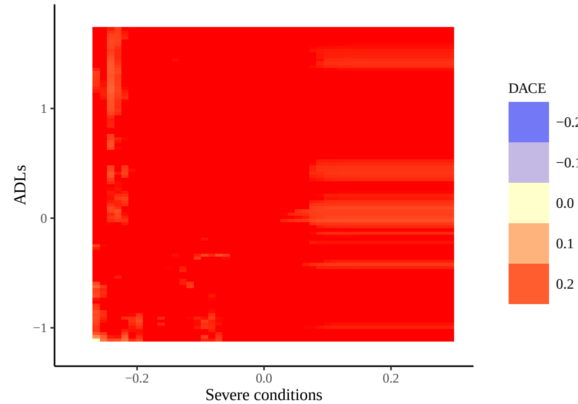
Panel 1: Couple Households



(A) Lower confidence band

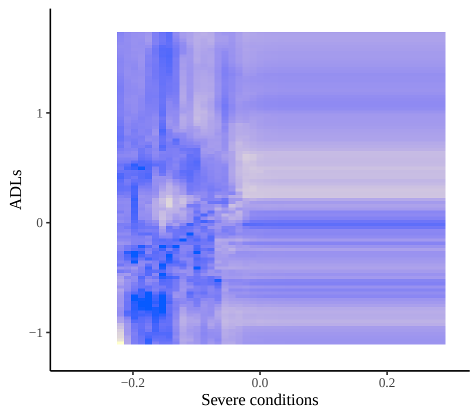


(B) Mean

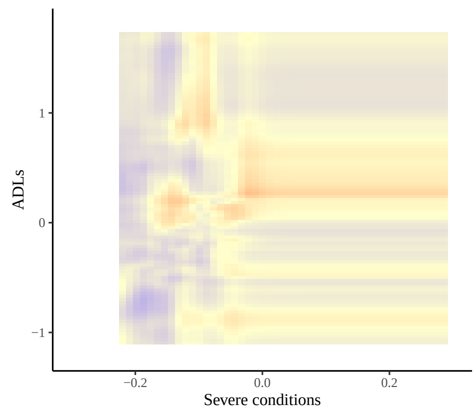


(C) Upper confidence band

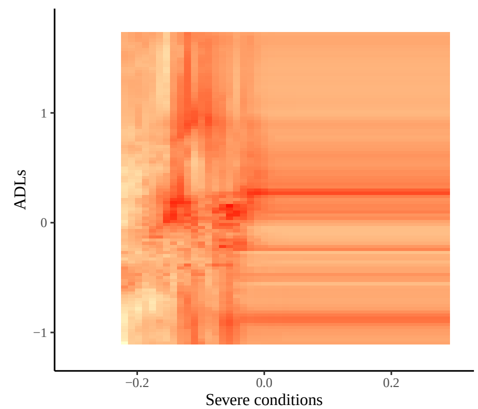
Panel 2: Single Households



(D) Lower confidence band



(E) Mean

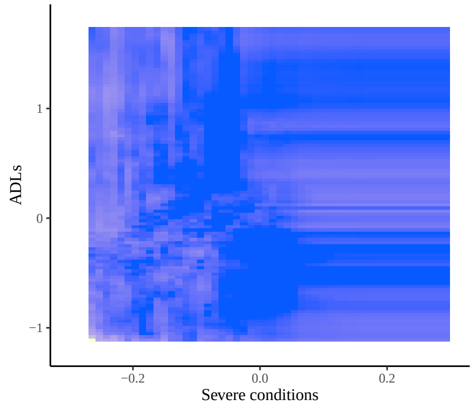


(F) Upper confidence band

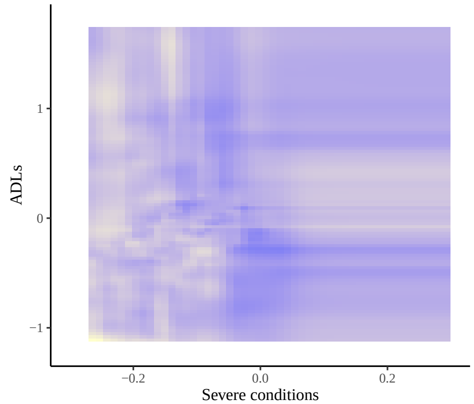
Figure E.3

Normalized DACE on Risky Asset Share using Severe Conditions and Activities of Daily Living

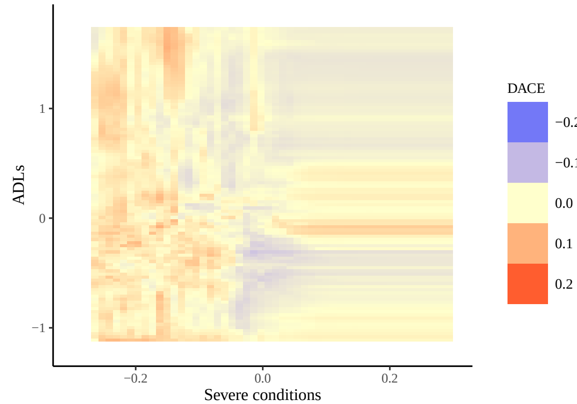
Panel 1: Couple Households



(a) Lower confidence band

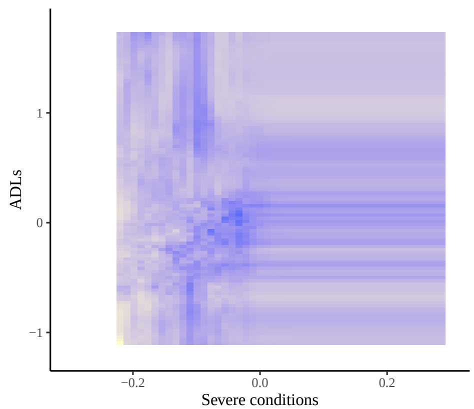


(b) Mean

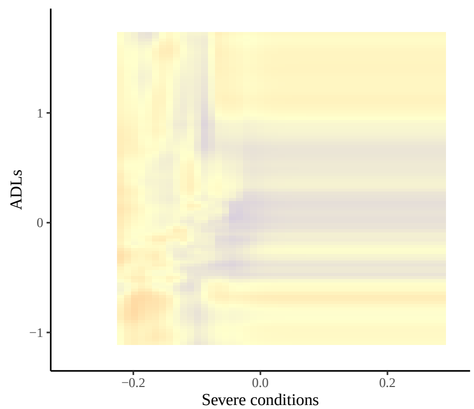


(c) Upper confidence band

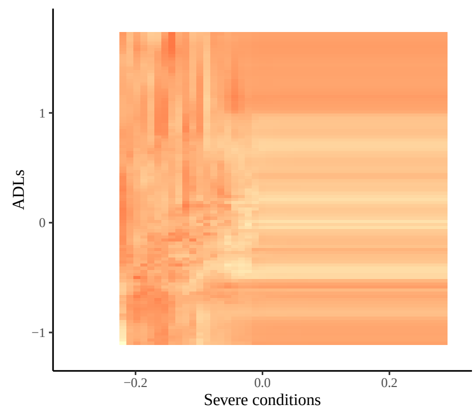
Panel 2: Single Households



(d) Lower confidence band



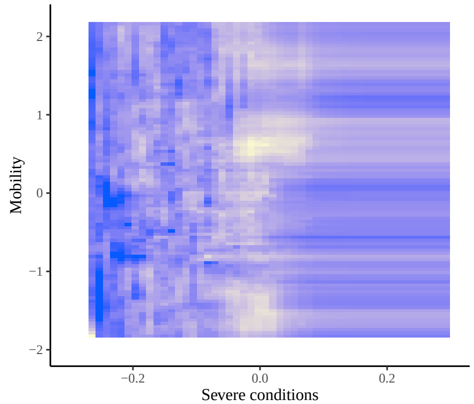
(e) Mean



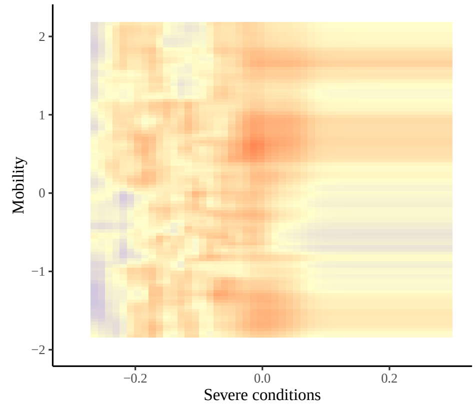
(f) Upper confidence band

Figure E.4
Normalized DACE on Safe Asset Share using Severe Conditions and Constraints to Mobility

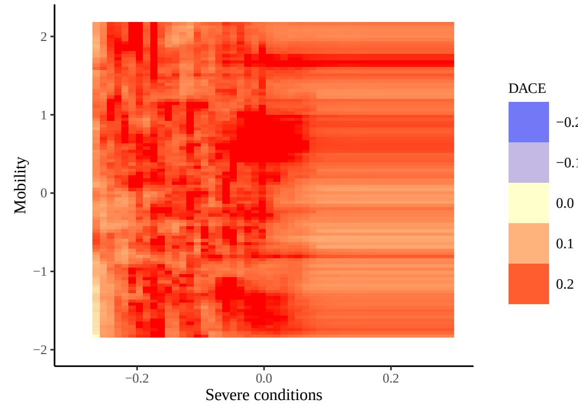
Panel 1: Couple Households



(a) Lower confidence band

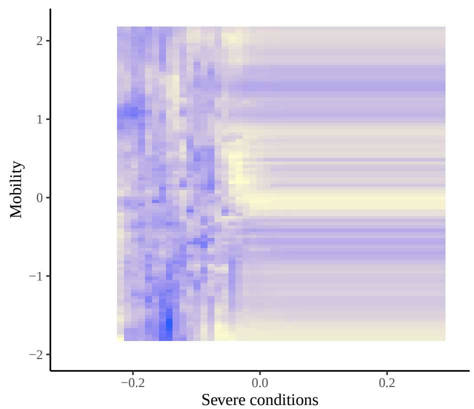


(b) Mean

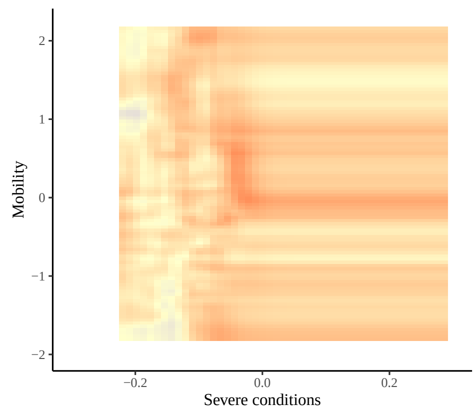


(c) Upper confidence band

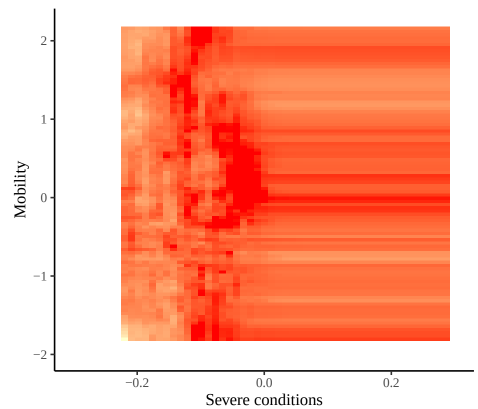
Panel 2: Single Households



(d) Lower confidence band



(e) Mean

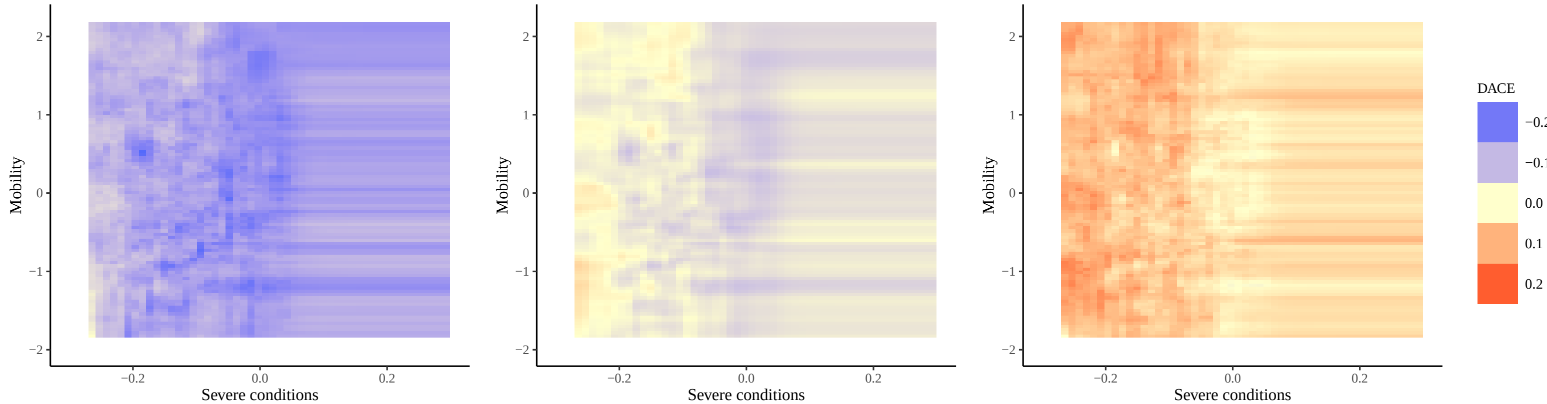


(f) Upper confidence band

FIGURE E.5

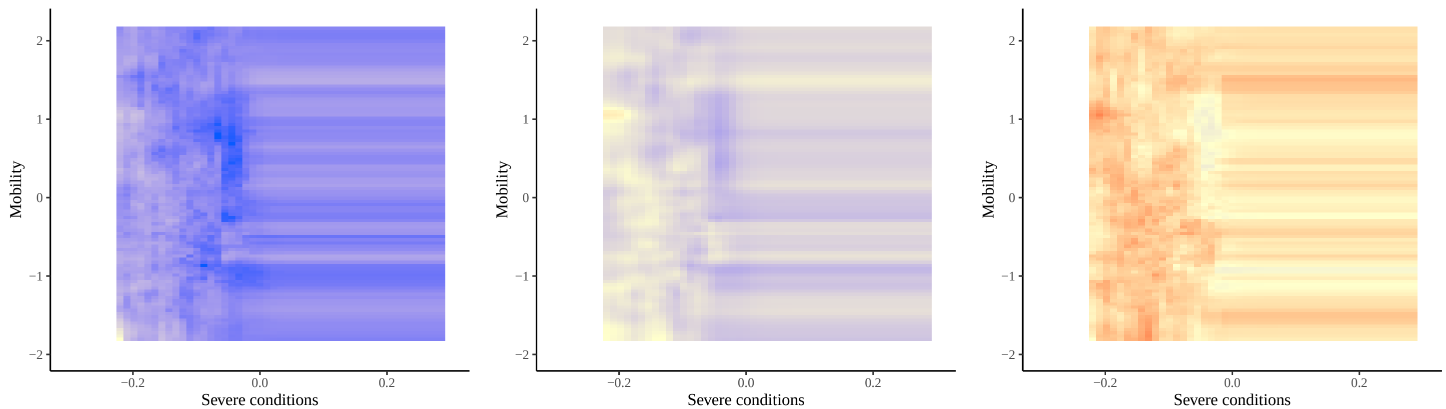
Normalized DACE on Risky Asset Share using Severe Conditions and Constraints to Mobility

Panel 1: Couple Households



(A) Lower confidence band (B) Mean (C) Upper confidence band

Panel 2: Single Households

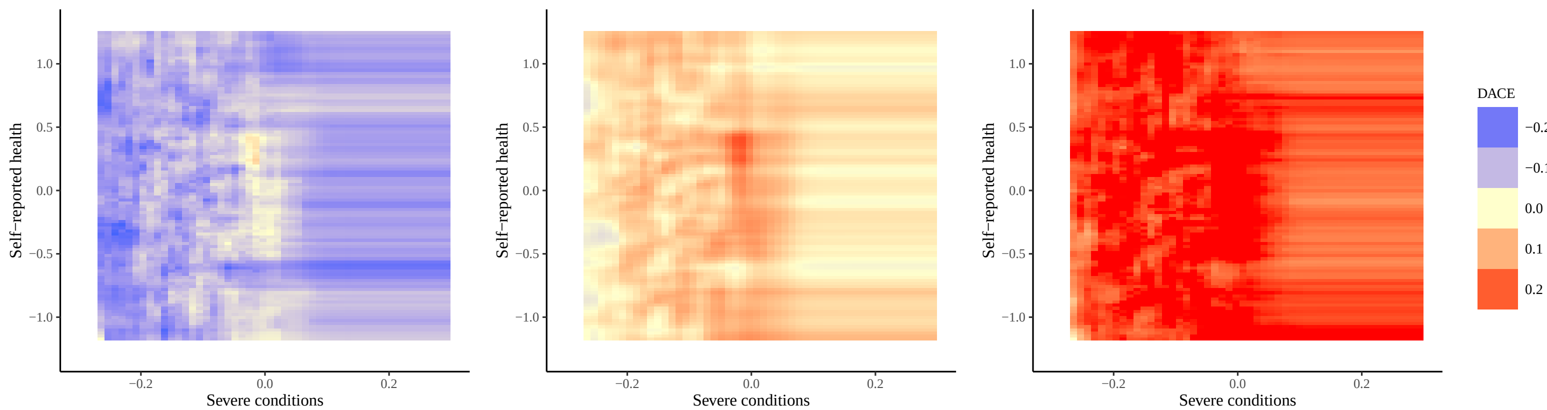


(D) Lower confidence band (E) Mean (F) Upper confidence band

Figure E.6

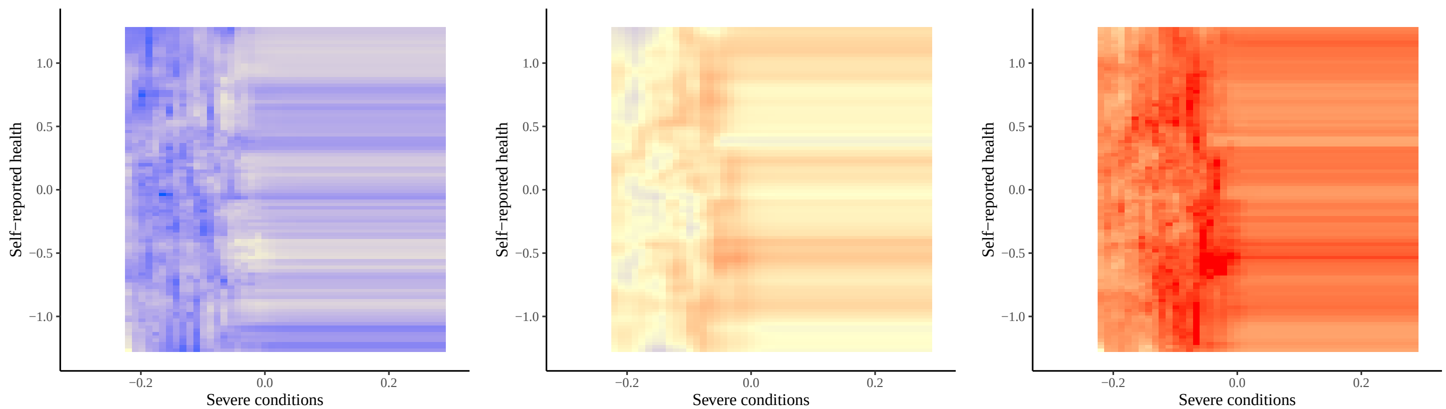
Normalized DACE on Safe Asset Share using Severe Conditions and Self-Reported Health

Panel 1: Couple Households



(A) Lower confidence band (B) Mean (C) Upper confidence band

Panel 2: Single Households

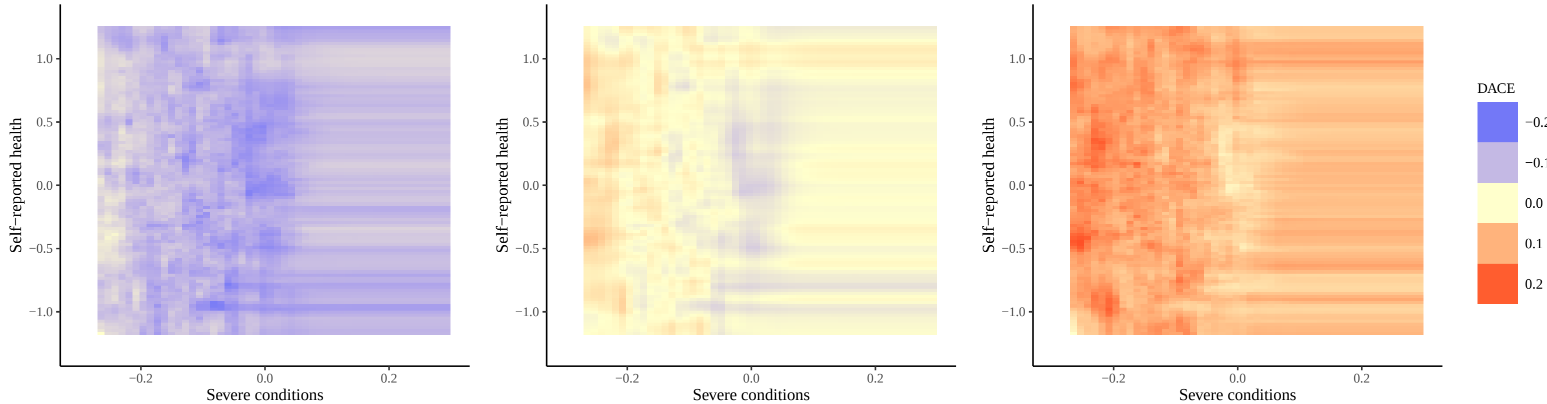


(D) Lower confidence band (E) Mean (F) Upper confidence band

Figure E.7

Normalized DACE on Risky Asset Share using Severe Conditions and Self-Reported Health

Panel 1: Couple Households

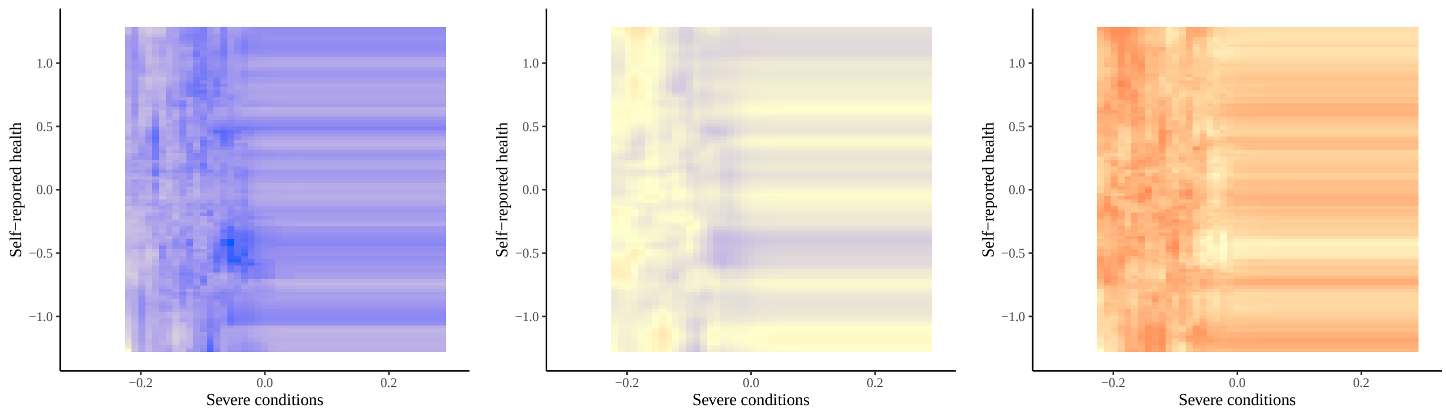


(A) Lower confidence band

(B) Mean

(C) Upper confidence band

Panel 2: Single Households



(D) Lower confidence band

(E) Mean

(F) Upper confidence band

F. Multiplicative-Interaction Estimation Results

This appendix considers the multiplicative-interaction estimation framework that arises under a linearity assumption on g as in equation (8). As argued in the main text of the paper, this linear framework imposes strong functional assumptions that can severely limit the extent to which heterogeneous effects of health care policy uncertainty can be captured. This is shown to be the case in the context of our paper.

The following figures show the estimated differences in conditional average causal effects (DACE) of health care policy uncertainty on safe and risky asset share, respectively, using the multiplicative interaction specification as in equation (8), for all five health categories considered in the paper. As before, the figures are normalized such that all estimates are relative to the conditional average causal effect of households that are substantially healthier than expected, which we define as having a more favorable unexpected change in the respective health category than 95% of households in the sample.

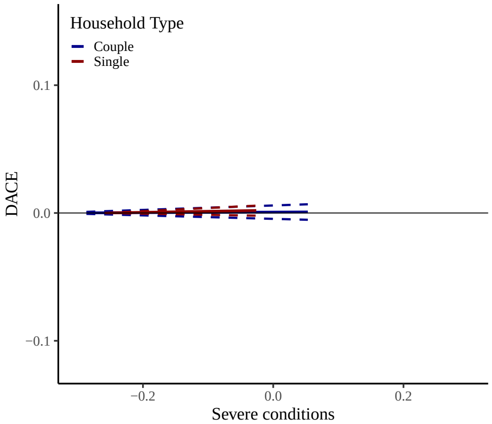
Figure F.1 presents estimates of the difference in conditional average causal effects based on unexpected changes to severe conditions (top panels) and on unexpected changes to nights spent in hospital (bottom panels) based on the multiplicative-interaction specification. The figure is thus analogous to Figure 2 with the only difference being the functional form assumption. Figure F.2 presents analogous estimates for the other three health categories, ADLs (top panels), mobility (center panels), and self-reported health (bottom panels).

In stark contrast to the semiparametric estimates, the restricted estimates of the difference in conditional average causal effects do not indicate substantial heterogeneity across different values in unexpected changes to health. Note further that because the bounds on the average causal effect are based on integrating the relative distribution of these effect-differences, the bound derived from these estimates would be close to zero and hence does not carry substantial information.

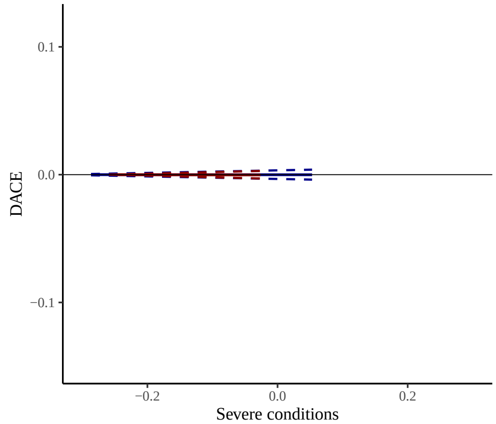
In the context of our paper, the functional form assumption imposed by a multiplicative interaction specification thus severely limits the possibility for deriving informative bounds on the average causal effect of health care policy uncertainty.

FIGURE F.1

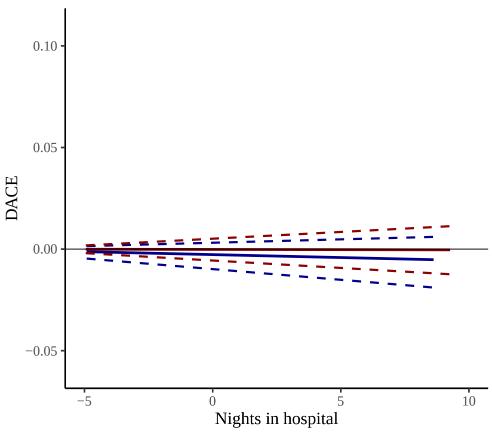
Normalized Linear DACE Estimates for Couple and Single Households



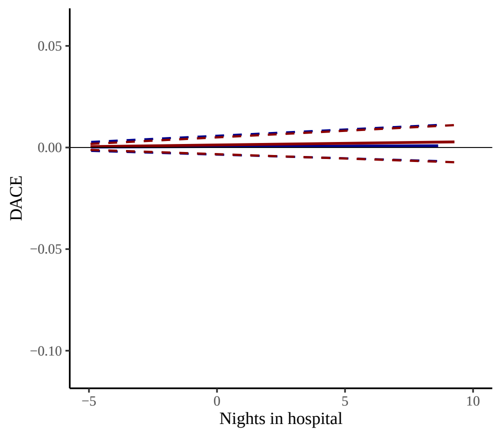
(A) Safe asset share



(B) Risky asset share

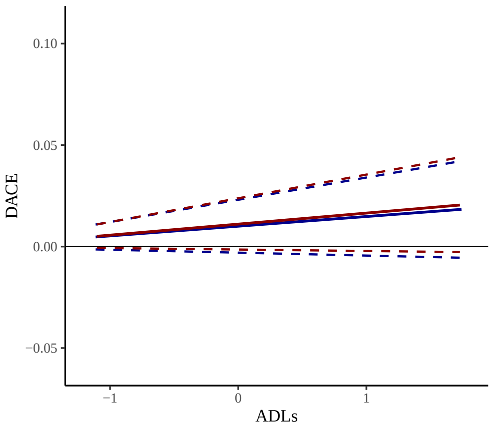


(C) Safe asset share

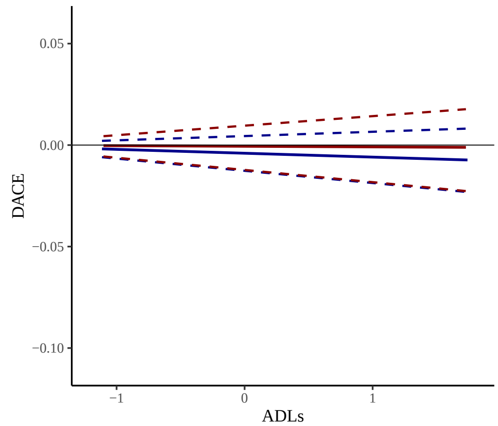


(D) Risky asset share

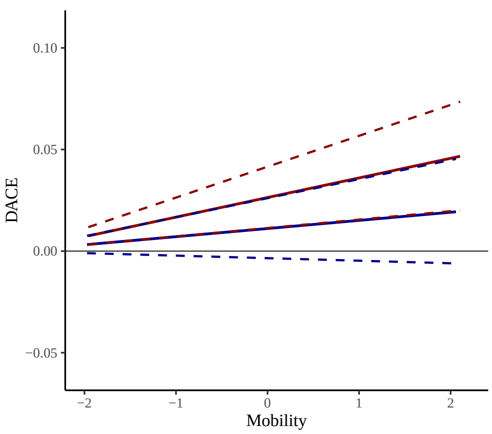
Figure F.2
Normalized Linear DACE Estimates for Couple and Single Households (Contd.)



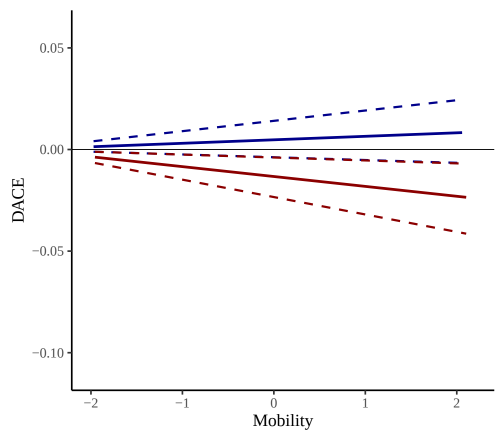
(a) Safe asset share



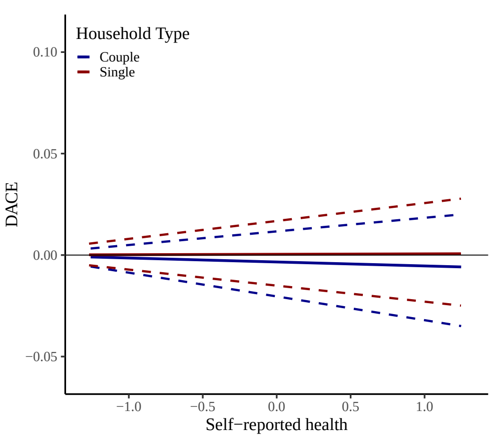
(b) Risky asset share



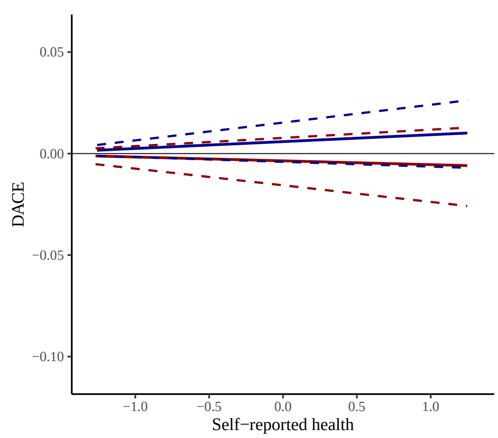
(c) Safe asset share



(d) Risky asset share



(e) Safe asset share



(f) Risky asset share

G. Results on Consumption

This appendix provides supplemental results on the effect of health care policy uncertainty on households' consumption expenditures.

To measure spending we exploit variation in households' consumption expenditures in line with Gruber and Yelowitz (1999). Data for this purpose are taken from the CAMS, which documents a variety of spending variables that are not included in the core HRS. In particular, we focus on households' total spending during the previous year. We consider both durable and total consumption expenditures, normalized to 2010 dollars.

As with the main analysis sample, we remove those households that are missing one or more of the variables used in estimation, or only occur in a single wave, leaving an analysis sample of 12,636 single and 8,116 couple household-wave observations. Appendix B provides detailed documentation of the cleaning steps and the associated reduction in sample at each stage.

We apply the same methodological approach to identify a bound on the average causal effect of health care policy uncertainty on household consumption expenditures as we did when investigating relative demand in risky assets. Notice, however, that the arguments derived from the background risk literature to motivate a bound on the conditional average causal effects on relative risky asset demand do not immediately transfer to consumption expenditures. Instead, for this application we draw from the extensive literature on precautionary savings (e.g., Zeldes, 1989; Kimball, 1990). Under the assumption of (sufficiently strong) risk aversion, theoretical insights from the precautionary savings literature imply an upper bound of zero on the conditional average causal effect of health care policy uncertainty on consumption expenditures – that is, given an increase in health care policy uncertainty, households, on average, do not increase their consumption.[4]

Table G.1 provides the bounds on the average causal effect of health care policy uncertainty on consumption expenditures. The effects signs are largely in line with expectations,

[4]Note that the assumptions for a precautionary savings mechanism are stronger than for a background risk mechanism. In particular, additional conditions are needed for the third derivatives of the utility function (rather than just the second). See Zeldes (1989) and Kimball (1990).

and hint at a moderate decrease in consumption expenditures when faced with an increase in health care policy uncertainty. However, none of the estimated bounds differ from zero at a 5% significance level. Due to the substantially smaller sample size and measurement complications of the dependent variables, we caution against interpreting these findings as definitive evidence against a precautionary savings effect of health care policy uncertainty.

TABLE G.1
Bounds on the Average Causal Effect on Consumption Expenditures

Durable Consumption		Total Consumption	
Couples (1)	Singles (2)	Couples (3)	Singles (4)
-33.4	-18.5	-2493.1	562.6
$(-\infty,\ 38.2]$	$(-\infty,\ 18.2]$	$(-\infty,\ 425.8]$	$(-\infty,\ 2303.1]$

Notes. The table presents estimates of the bound on the average causal effect of health care policy uncertainty on consumption expenditure, $E\left[\text{DACE}(x', x, H, \bar{h})\right]$,where $\bar{h}$ is defined here as having a more favorable unexpected change in each of the five health categories than 95% of households in the sample. Brackets contain one-sided confidence intervals covering 95% of bootstrapped bounds

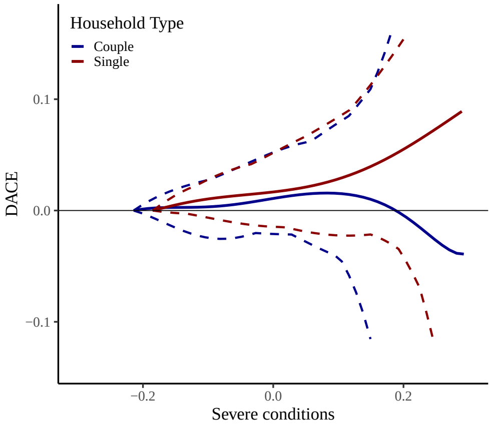
H. Robustness Results for Individuals with Age below 65

Because most individuals above age 65 in the United States have Medicare, one might suspect that for these individuals, health care policy uncertainty would have less of an effect on their portfolio decisions than for those below age 65.[5] For robustness, in this section the semiparametric estimation results are repeated, this time restricting the estimation to a sub-sample of households where no household member is 65 years old or older; these are shown in Figure H.1 for the two health categories presented in the paper in Figure 2 (severe conditions and nights in hospital) and Figure H.2 for the other three health categories (ADLs, mobility, and self-reported health, analogous to Figure E.1).[6] The result of this restriction is a fairly large reduction in sample. For couple households, this sample restriction leaves 25,584 of the initial 57,190 observations. For single households, this sample restriction leaves 15,157 of the initial 45,384 observations. A noticeable increase in the bias and variance of the estimates is therefore expected. Nonetheless, the results are largely similar to those using the full sample. In particular, the point estimates still suggest a decreased (increased) relative demand in risky (safe) assets with worsening unexpected changes in health. The local linear regression-based instruments are not significant for most health categories.

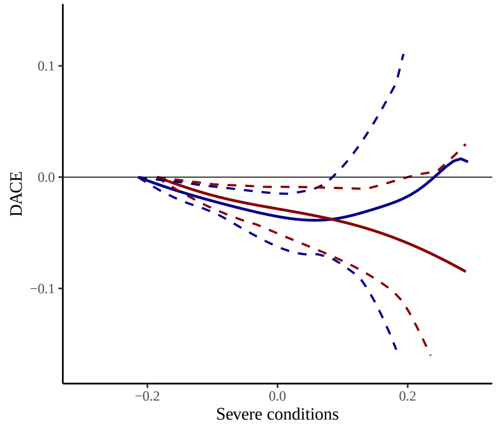
[5]Including individuals over 65 in the sample, as we do in the main paper, should, therefore, attenuate any measured effects.

[6]As before, these plots show the local linear regression-based estimates of differences in average causal effects of health care policy uncertainty on safe and risky asset share, respectively, conditional on a single health category, and the solid lines correspond to the mean and the dashed lines correspond to the bootstrapped 99% uniform confidence bands. The estimates are relative to the baseline of households that are in substantially better health than expected, defined here as having a more favorable unexpected change in the corresponding health category than 95% of households in the sample. The plots are based on $B = 1,000$ bootstrap draws.

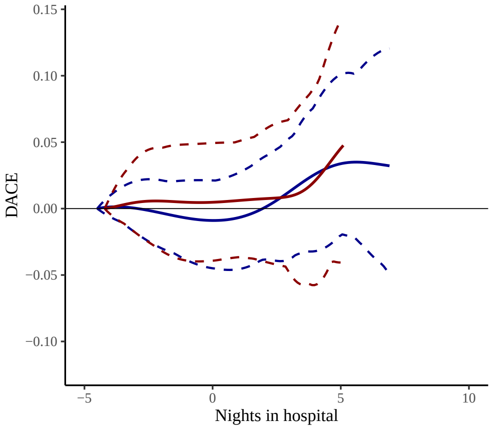
Figure H.1
Normalized DACE Estimates for Couple and Single Households (pre 65)



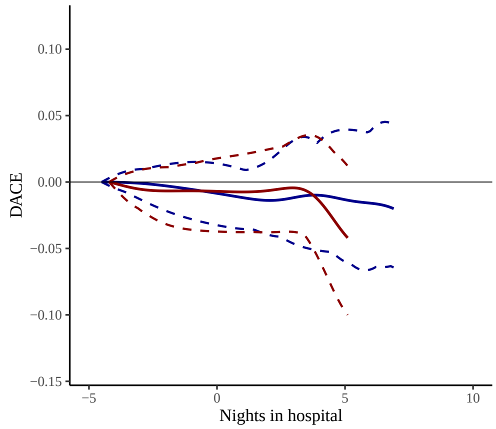
(A) Safe asset share



(B) Risky asset share

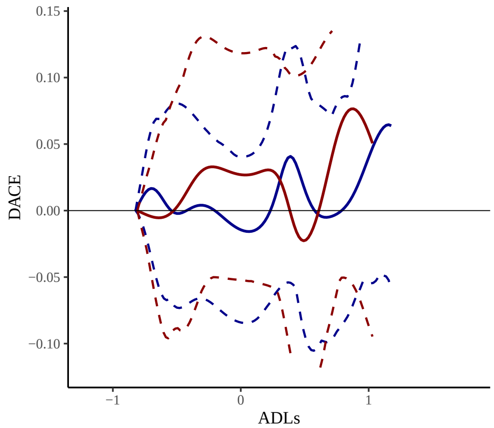


(C) Safe asset share

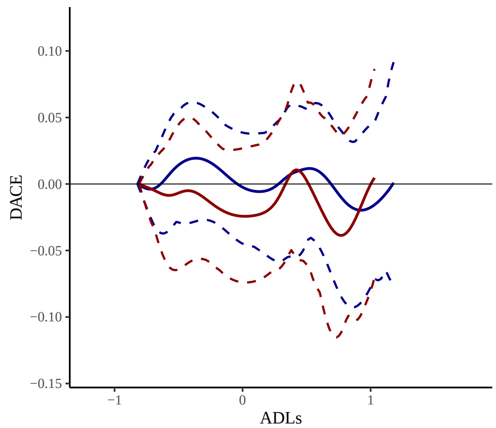


(D) Risky asset share

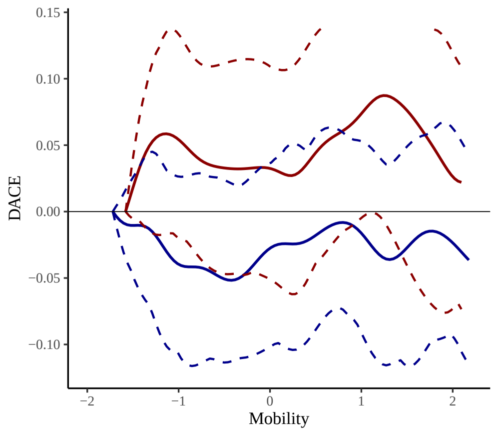
Figure H.2
Normalized DACE Estimates for Couple and Single Households (pre 65; contd.)



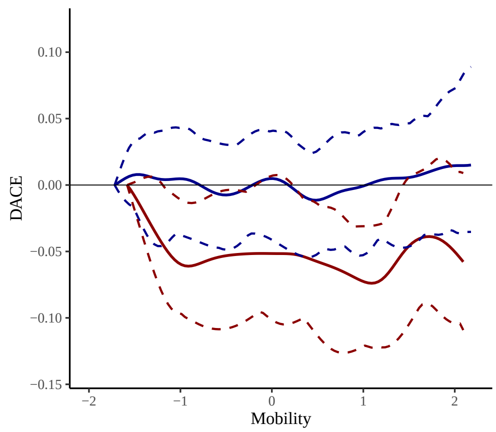
(A) Safe asset share



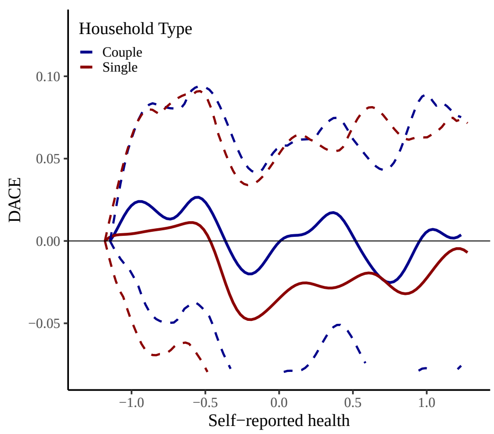
(B) Risky asset share



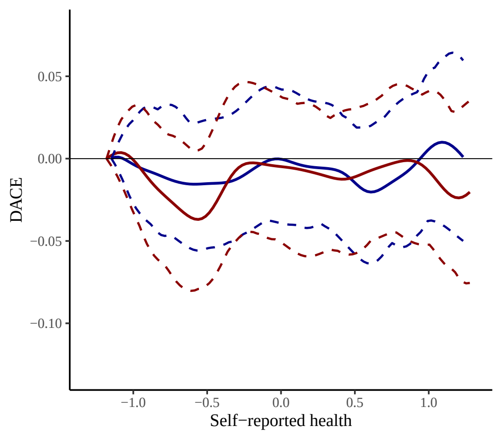
(C) Safe asset share



(D) Risky asset share



(E) Safe asset share



(F) Risky asset share