Erasmus University Rotterdam
Erasmus School of Economics
Bachelor Thesis BSc^2 Econometrics & Economics

Health Care Policy Uncertainty in the United States and its Effect on Households' Consumption and Portfolio Choice

Thomas Wiemann (411272)

Abstract

As a major topic of debate in the United States, health care reform is a primary cause for economic policy uncertainty. At the same time, medical expenditures are an increasingly important contributor to households' financial risk due to rising costs of treatment. Despite its apparent importance, this study is the first to assess the effect of health care policy uncertainty on households. I develop a simple theoretical model that predicts a negative effect of health care policy uncertainty on consumption and relative demand for risky financial assets. The model also illustrates that the health care policy uncertainty effect can be expected to increase with bad health. Using the HRS' rich longitudinal data on older Americans and Baker et al.'s (2016) recently developed health care policy uncertainty index, these claims are tested using Honoré's (1992) semiparametric fixed effect censored regression estimator, a concomitant-variable latent class Tobit model, and a Tobit model-based recursive partitioning procedure. The results do not indicate an economically relevant effect of health care policy uncertainty on households' consumption. However, I find substantial empirical evidence for an important effect on households' portfolio choice and suggestive evidence that the effect is increasing in households' health problems. These results are robust to model specification and do not appear to be caused by potentially endogenous household characteristics (e.g., wealth) or confounding types of uncertainty (e.g., business cycle uncertainty).

Supervisor: Prof.dr. Robin Lumsdaine
Second Assessor: Dr. Andrea Naghi

July 8, 2018

Acknowledgements*

My gratitude goes out to Professor Robin Lumsdaine, who motivated me to pursue an economic topic and an empirical approach that I am truly interested in. Without her comments and suggestions, the quality of this thesis would not have been possible. I would also like to thank Professor Richard Paap for encouraging me to participate in the Tinbergen Institute lectures by Professor Guido Imbens on the topic "Causal Inference and Machine Learning" and the subsequent workshop of the Econometric Institute under the same title, where I gained much inspiration for the econometric models employed here. Finally, I am very grateful to my peers Hugo Galy, Patricia Wahren and Alicia Curth for making me look forward to the early mornings and late nights in the library. All remaining errors are my own.

*In consultation with Professor Lumsdaine, this thesis does not explicitly replicate the results of the reference paper Baker et al. (2016). Instead, I am fully committed to the economic and methodological extension. The reasons for this decision are outlined in Appendix E.

Contents

1 Introduction

Eight years after the enactment of the Affordable Care Act, health care policy remains a central topic of political debate in the United States (Johnson, 2017)[1]. A recent example is the heatedly fought over repeal-and-replace attempt of the 2010 law in 2017, which was meant to fulfil a central promise of then-Candidate Trump's presidential campaign (Suderman, 2017). It is thus not surprising that Baker et al. (2016) find health care reform to be the second largest source of policy uncertainty in the US, short only behind fiscal policy. At the same time, medical expenditures are becoming an increasingly important contributor to households' financial risk: between 1990 and 2018, health spending rose from 15% to 21% of total personal consumption expenditures (Bureau of Economic Analysis, 2018). As the welfare effects of policy uncertainty are particularly substantial when the policy has a potentially large impact on households' consumption abilities (Luttmer & Samwick, 2018), health care policy uncertainty is likely to be a major source of policy uncertainty-caused welfare loss. Yet, the effect of uncertainty about health care reform remains unassessed. This study attempts to fill this gap. The results are interesting, not only because they shed light upon the economic behaviour of households, but also because they point to real macroeconomic consequences of health care policy uncertainty. The latter attaches previously overlooked costs to the highly polarised political discussions on health care reform in recent years, which seem relevant for both legislatures and voters.

Existing economic literature suggests that households likely react to health care policy uncertainty along two dimensions; consumption and portfolio choice. The first relates to the work on *precautionary savings*. Theoretical buffer-stock models predict that households' consumption decreases when faced with an uncertainty shock, not only because their expected income could be affected, but also to self-insure against income risk (e.g., Carroll, 1997; Kimball, 1990b; Zeldes, 1989). The second relies on the characterisation of policy uncertainty as an uninsurable risk largely beyond one's control. In the presence of such *background risk*, existing theoretical research predicts a decreased willingness of households to endure other types of risk, including rate-of-return risk (e.g., Gollier & Pratt, 1996; Kimball, 1993; Pratt & Zeckhauser, 1987). Both dimensions have also been empirically investigated in the context of economic (non-health care specific) policy uncertainty. Aaberge et al.'s (2017) and Giavazzi and McMahon (2012) findings support the claim that households save more in times of political uncertainty, and Agarwal et al. (2018) and Gábor-Tóth and Georgarakos (2018) confirm the predicted decrease in investment in risky financial assets. In related work on uncertainty about Social Security benefits, Delavande and Rohwedder (2011) provide evidence that higher subjective uncertainty is negatively associated with investment share in stocks. Being a relatively recent strand of literature, however, research on the effect of policy uncertainty suffers from some qualifications.

A pivotal point of discussion in research on policy uncertainty is the identification of *causal* effects. Among the most convincing and popular identification strategies in the literature is the exploitation of variation in uncertainty exposure. For example, in their study of Germany's 1998 national election, Giavazzi and McMahon (2012) argue that civil servants were not affected by the candidates' policy differences and are thus a suitable control group for a difference-in-

[1] President Obama (2016) reviews the act as the most important health care reform since the creation of Medicare and Medicaid in 1965. A reference of the law is provided under United States Congress (2010).

difference design. While the authors present supporting anecdotal evidence, some doubts remain about whether the variation in policy uncertainty exposure is unrelated to variation in exposure to economic uncertainty, and what this implies for inference on causal effects.

Additionally, current literature does not grant explicit theoretical illustrations of possible effect-channels of policy uncertainty on households' economic decisions. Instead, expectations are often based on research on the effects of general, non-policy related economic uncertainty. Especially as the differentiation of policy uncertainty effects and economic uncertainty effects is essential for causal inferences in empirical research, a model that illuminates the impact of *policy* uncertainty on households' consumption and financial behaviour seems overdue.

This study makes several contributions to complement existing research and address some of its shortcomings. First, to the best of my knowledge, this is the first attempt to assess the impact of health care policy uncertainty on households. For this purpose, I merge longitudinal household data from the 1992-2014 waves of the Health and Retirement Study with Baker et al.'s (2016) recently developed health care policy uncertainty index. Second, this study takes a novel approach in the policy uncertainty literature by exploiting health differences for identification of causal effects. This variation in exposure to policy uncertainty has several advantages as confoundedness with variation to economic uncertainty is less prevalent compared to previous studies' strategies. Third, I develop a simple two-period consumption and portfolio choice model for theoretical illustration of the potential health care policy uncertainty effect.

Finally, I implement some methodological improvements. Contrasting the linear regressions in the existing policy uncertainty literature, this study employs Honoré's (1992) fixed effect censored regression estimator to account for the asymmetric nature of households' consumption and financial asset investment. Due to concerns regarding the commonly employed multiplicative-interaction specification, I consider two alternatives for assessing whether the magnitude of the policy uncertainty effect is associated with households' health. The first considers a concomitant-variable latent class Tobit model as an extension of a finite mixture model, the latter being a common technique for analysing hidden (causal) structures. While allowing for inference on parameter heterogeneity even in cases with weak (or no) association of observed variables and mixture components, estimation of the latent class model requires substantial coefficient differences. A complementary approach is given by Zeileis and Hornik's (2007) model-based recursive partitioning procedure. The method splits (rather than 'mixes') the sample into disjoint partitions to account for parameter instability along a set of features. Albeit similar in interpretation to the latent class model, the method allows assessment of even slight parameter differences when components are strongly related to observed variables (Frick et al., 2014). I incorporate a Tobit model and modify the splitting-criterion to adapt the procedure for the question of interest. In doing so, this study contributes to the recent developments on the application of machine learning in economics (e.g., Athey & Imbens, 2017) by being the first to highlight the broad applicability of model-based recursive partitioning despite the presence of asymmetric outcomes and non-binary, potentially confounded variables of interest[2].

[2]Zeileis et al. (2008) are widely cited in the machine learning, statistics, and medical literature. Yet, to the best of my knowledge, the only application in economics is Wagner and Zeileis (2018) – a paper of the author in the *German Economic Review* – where the procedure is merely discussed in the context of OLS.

Despite statistically significant estimates, the results do not indicate an economically relevant effect of health care policy uncertainty on households' consumption. However, the empirical results highlight an important link between health care policy uncertainty and their portfolio choice. In particular, households decrease their share in risky financial assets by approximately 1 percentage-point when faced with an uncertainty increase similar to the increase from 2016 to 2017. Further evidence suggests that the effect of health care policy uncertainty is more substantial for households with worse health. The findings are robust to model specification and incorporation of household- and macro-level controls. As these estimates are comparable in size to a decrease in health (e.g, Rosen & Wu, 2004), this study indicates that health care policy uncertainty is an important determinant of households' financial behaviour.

The paper proceeds as follows: Section 2 reviews relevant literature and develops a simple theoretical model on the effects of health care policy uncertainty. Section 3 describes the data and the applied transformations. Section 4 illustrates the empirical strategy. Section 5 presents the results. Section 6 discusses their implications with some suggestions for future research.

2 Literature Review and Theoretical Framework

This research draws from, and complements, three strings of economic literature: theoretical and empirical work on precautionary savings and portfolio choice in the context of income risk, empirical research on the effects of health and medical expenditure risk, and the recent studies on the implications of policy uncertainty for households' economic behaviour. This section discusses each in the following, and concludes with a simple theoretical model on health care policy uncertainty and households' consumption and portfolio choice.

Precautionary savings have been extensively analysed in the context of income uncertainty. Savings behaviour unaccounted for by conventional life cycle models was first explained by 'buffer-stock' models (e.g., Carroll, 1997; Kimball, 1990b; Zeldes, 1989). Their main prediction is that consumption is not only related to expected income, as predicted by the life cycle model, but also to higher moments such as income variance. Empirical research, however, has led to ambiguous conclusions on the importance of income uncertainty-caused savings, as estimates range from insubstantial (e.g., Guiso et al., 1992; Skinner, 1988) to economically relevant (e.g., Carroll & Samwick, 1998; Fuchs-Schündeln & Schündeln, 2005). The similarly vast literature on background risk provides insights into households' portfolio choice in an environment of multiple risks. Theoretical models of, for example, Gollier and Pratt (1996), Kimball (1993), and Pratt and Zeckhauser (1987) and predict that households exposed to an undiversifiable risk are less willing to bear other types of risk, including rate-of-return risk (Goldman & Maestas, 2013). Supporting empirical evidence is provided by, for example, Guiso et al. (1996), who find that income uncertainty decreases the demand for risky financial assets.

Why might health care policy uncertainty affect the consumption and financial behaviour of households in a similar manner as 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 pose as a risk on spending needs with potentially similar implications as income risk. While health care policy uncertainty has not been analysed, the claim that uncertainty in spending needs affects households' consumption and financial behaviour finds large support in existing research on health and medical expenditure risk.

Early research on the effect of health risk indicated a substantial negative effect on the demand for risky assets (e.g., Berkowitz & Qiu, 2006; Edwards, 2008; Rosen & Wu, 2004). However, some recent studies refute these findings. After controlling more thoroughly for unobserved heterogeneity, no or only small effects of health risk can be found (e.g., Fan & Zhao, 2009; Love & Smith, 2010). Because health might not only affect spending needs but also households' expected lifespan and consumption utility, the interpretation of these results provides some challenges (Edwards, 2008; Smith, 1999). For a more direct estimate on the financial burden of health, other research exploits variation in households' exposure to medical expenditure risk through their insurance coverage. Using exogenous variation in Medicaid eligibility, Gruber and Yelowitz (1999) find that households' medical expenditure risk exposure has a strong negative association with consumption[3]. With a similar identification approach, Goldman and Maestas (2013) find that relative demand for stocks increases as medical expenditure risk decreases. Further supporting evidence is provided by Atella et al. (2012), who find that health shocks have a significantly negative effect on portfolio choice in European countries without universal health care, while discovering no evidence for an effect in other European countries.

Although health and medical expenditure risk through insurance coverage are closely related to health care policy uncertainty in their implications for consumption and portfolio choice, they are distinct sources of risk. In particular, households can affect their health (e.g., by deleterious behaviours such as smoking) and their insurance coverage (e.g., through private insurance plans), yet, individual households cannot meaningfully influence the national debate on health care reform. On one hand, analysing macroeconomic health care policy uncertainty alleviates endogeneity concerns caused by the positive associations between households' health and insurance coverage with their wealth or education (e.g, Smith, 1999)[4]. On the other hand, this foregrounds concerns on potential confoundedness with other macroeconomic sources of uncertainty. For example, Bloom (2014) shows that policy uncertainty is strongly correlated with economic business cycles. As economic contractions are linked to higher economic uncertainty and lower investment prospects, their neglect could lead to substantially over-estimated effects of policy uncertainty. In general, *health care* policy uncertainty can be expected to be less confounded by economic uncertainty. For example, in contrast to the fiscal policy analogue, *counter-cyclical* health care reform seems rare. Nevertheless, a strong claim for causal effects requires careful consideration of potentially confounding factors.

The recent literature on the effect of policy uncertainty on households provides some insights on how to address this issue in the empirical approach. Investigating Germany's 1998 national election, Giavazzi and McMahon (2012) argue that the increase in savings and labour supply they identify is caused by heightened policy uncertainty rather than economic uncertainty, as

[3] In contrast, Starr-McCluer (1996) claims that higher savings are linked to *lower* medical expenditure risk. As risk exposure is assessed by (endogenous) health insurance enrolment, however, doubts remain as to whether the findings do not reflect the positive association of insurance and wealth instead.

[4] This is a substantial issue for identification in previous literature. 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 and health coverage requires crafty estimation approaches through, for example, quasi-random variation in subsidised health insurance eligibility (e.g., Goldman & Maestas, 2013; Gruber & Yelowitz, 1999) or identification of suitable instruments (e.g., Love & Smith, 2010).

Germans were likely optimistic about the economy during that time. Unfortunately, similar anecdotal reasoning is difficult to substantiate empirically for the 23-year period considered in this study. Aaberge et al. (2017) corroborate the positive effect of policy uncertainty on households' savings by exploiting a major political shock in China. While the authors account for seasonal confounding by correlating the monthly saving differences in the year of the shock with differences in the subsequent year, it is unlikely that such a monthly effect is generally sufficient to account for confounding economic uncertainty. Alternatives are suggested in the ongoing work of Agarwal et al. (2018) and Gábor-Tóth and Georgarakos (2018), who provide evidence that policy uncertainty decreases relative demand for risky assets. In particular, Agarwal et al. (2018) control for national business cycles by exploiting temporal variation in gubernatorial elections across US states, and Gábor-Tóth and Georgarakos (2018) explicitly account for various measures for economic uncertainty such as the implied volatility index of the S&P 500 index (VIX) as suggested by Bloom (2014). As elections are not generally concerned with only a single political issue such as health care reform, the latter approach seems to be most suitable for this study to address any potential confoundedness with other forms of macroeconomic uncertainty.

As illustrated above, numerous existing studies suggest a negative effect of health care policy uncertainty on households' consumption and relative demand for risky financial assets. Yet, explicit theoretical and empirical evidence has yet to be presented. The simple household model developed in the subsequent section is a first attempt at the former.

2.1 A Simple Household Model on Health Care Policy Uncertainty

In the following, I develop a simple two-period model on the link between health care policy uncertainty and households' consumption and portfolio choice. As will become evident, it is not the purpose of the proposed model to provide a complete overview of consumption and financial behaviour in the presence of uncertainty[5]. Instead, its aim is to provide an illustration of a possible effect-channel of policy uncertainty and to allow for derivation of testable hypotheses.

The model draws from the general idea of Elmendorf and Kimball (2000), who develop a two-period model to investigate the effect of income uncertainty on individuals' consumption and demand for risky financial assets, but differs in the definition of uncertainty. Instead of income risk, individuals of this model are subject to risk in spending needs due to uncertainty in health care treatment cost. Further, rather than considering a continuous random state space, I consider a discrete random variable. The latter simplification is similar to that of Delavande and Rohwedder's (2011) two-period model on portfolio choice under Social Security uncertainty.

The following structure applies. At the beginning of period 1, the individual is endowed with initial wealth W_0 and health that requires H units of treatment. She decides how much of current wealth is consumed immediately (C_1), what share $(1-x)$ of her remaining wealth is invested in the safe asset with return b, and what share (x) is invested in the risky asset. The latter has a return of r_1 at subjective probability p_1 and a return of r_2 at subjective probability $p_2 = 1 - p_1$. It is assumed that the expected return of the risky asset is larger than that of the safe asset – that is, $p_1 r_1 + p_2 r_2 > b$ – and that $r_1 < b < r_2$. In period 2, the risky asset's

[5]For more thorough theoretical investigations of these topics, consider, for example, Bodie et al. (1992), Zeldes (1989), Carroll (1997), Elmendorf and Kimball (2000), or Chacko and Viceira (2005).

return has been determined and the individual consumes her realised wealth minus her health cost given by $H * P$, where P is the cost per unit of health care treatment in period 2. It is useful to first consider the case where the treatment costs are known and fixed.

The individual is assumed to choose her initial consumption C_1 and share invested in risky assets x in order to maximise her expected utility given by $E[U(C_1) + U(C_2)]$, where $U(C)$ is differentiable in C. As common in much of the theoretical literature, the individual is assumed not to have a bequest motive (e.g., Levin, 1995). Thus, the individual solves the problem

$$\max_{(C_1,x)} E[U(C_1) + U(C_2)] = U(C_1) + p_1 U(C_2^1) + p_2 U(C_2^2), \tag{1}$$

where $0 \leq C_1 \leq W_0$, $0 \leq x \leq 1$, and $C_2^i = (W_0 - C_1)(1 + xr_i + (1 - x)b) - H * P$ for $i = \{1, 2\}$.

Next, consider the cost per unit of health care treatment that the individual faces in period 2 to be uncertain. Specifically, suppose that the per-unit cost is P_1 with subjective probability p_1^H and P_2 with subjective probability $p_2^H = 1 - p_1^H$. Here, I assume that the expected value of the cost of treatment is equal to the cost of treatment under certainty – that is, $p_1^H P_1 + p_2^H P_2 = P$ – and that $P_1 > P_2$. The random return of the risky asset and the random per-unit treatment cost are both determined at the beginning of period 2, hence, there exist four random states $(i, j) \in \{1, 2\} \times \{1, 2\}$ with corresponding probabilities $P\big[\mathcal{S} = (i, j)\big] = p_{ij} = p_i p_j^H$. For simplicity, it is assumed that there is no correlation between returns of the risky asset and per-unit cost of treatment[6]. Maximising expected utility, the individual then solves

$$\max_{(C_1,x)} E[U(C_1) + U(C_2)] = U(C_1) + p_{11} U(C_2^{11}) + p_{12} U(C_2^{12}) + p_{21} U(C_2^{21}) + p_{22} U(C_2^{22}), \tag{2}$$

where $0 \leq C_1 \leq W_0$, $0 \leq x \leq 1$, and $C_2^{ij} = (W_0 - C_1)(1 + xr_i + (1 - x)b) - H * P_j$ for $(i, j) \in \{1, 2\} \times \{1, 2\}$.

To allow for inference on the impact of uncertainty in the per-unit cost of treatment, it is necessary to impose some structure on the utility function $U(\cdot)$. In line with much theoretical work, I assume that $U(\cdot)$ is monotonically increasing and strictly concave (i.e., $U'(\cdot) > 0$ and $U''(\cdot) < 0$, with superscripts denoting the order of derivative). Further, the utility function displays *decreasing absolute risk aversion* defined by $\frac{\partial}{\partial z}\big[\frac{-U''(z)}{U'(z)}\big] < 0$. Being a necessary condition for risky asset investment to be positively associated with wealth, this is a standard assumption with large empirical basis (Elmendorf & Kimball, 2000). Finally, I assume *decreasing absolute prudence* given by $\frac{\partial}{\partial z}\big[\frac{-U'''(z)}{U''(z)}\big] < 0$. Decreasing absolute prudence has the implication that the absolute strength of the precautionary savings motive decreases with wealth. As discussed in Elmendorf and Kimball (2000) and Kimball (1990a, 1990b), this assumption is not particularly constraining on the utility function – it is already satisfied by the commonly used utility functions with decreasing absolute risk aversion – and is a plausible a priori condition[7]. The model and

[6]Elmendorf and Kimball (2000), using a similar model, discuss the possibility of correlation between the rate-of-return risk and the income risk in some detail. In line with their derivations, a positive correlation between the risk in r and the risk in P magnifies the results of the model developed here.

[7]Elmendorf and Kimball (2000) and Kimball (1990a) motivate decreasing absolute prudence with an example: Consider a professor with a wealth of \$10,000 and Rockefeller with a wealth of \$10,000,000. If both have same preferences except for their differences in initial wealth, who will save more after being told that they will loose \$5,000 at 50% chance at the end of the year? As the professor is intuitively expected to save more, this provides

the assumptions on the utility structure then imply the following results:

Proposition 1. *When exposed to uncertainty about the health treatment cost, the individual reduces consumption in period 1 and reduces her relative risky asset investment (if $H > 0$).*

Proposition 2. *The magnitudes of the consumption reduction in period 1 and the risky asset share reduction are positively associated with bad health (i.e., higher H).*

Proof. The proof of Proposition 1 and 2 is given in Appendix A.

This simple model points to theoretical evidence for a negative effect of health care policy uncertainty on households' consumption and relative demand for risky assets (or; a positive effect on savings and relative demand for safe assets). Further, bad health seems to magnify this effect. Section 5 investigates the existence of empirical evidence for these theoretical claims.

Finally, it is in order to discuss some of the model's most important simplifications. First, there is no possibility for increased income in period two through, for example, labour supply adjustment as in Bodie et al. (1992) and Delavande and Rohwedder (2011). Allowing for this additional dimension, however, is likely to strengthen the results derived here. As healthier individuals are likely to be more flexible in their labour activities than those less healthy, the former can more easily compensate potential spending need increases in period 2, and are thus more willing to take other risks (Bodie et al., 1992). Second, it is assumed that individuals value consumption in period 1 and 2 equally. If consumption in period 2 is discounted, the effect of uncertainty about the per-unit cost of treatment will be lower in magnitude. Importantly, however, the direction of the effect remains[8]. Third, health is assumed to solely impact the individual's medical expenditures. As illustrated by Smith (1999), health might also have a decreasing effect on her utility of consumption and her expected life span. In this case, worse health has similar effects as lower risk aversion and time preferences for consumption in the presence. For similar reasons that the effect of health risk on households' savings and portfolio choice is theoretically ambiguous (Goldman & Maestas, 2013; Smith, 1999), the effect on households' reaction to health care policy uncertainty might also be ambiguous if the decrease in consumption utility and/or expected lifespan has a comparable effect as the increase in medical expenditures. As empirical research provides mixed results on which effect of health is most pivotal (e.g., Berkowitz & Qiu, 2006; Love & Smith, 2010; Rosen & Wu, 2004), it is difficult to rate this assumption a priori without guidance by empirical results. Last, individuals are likely to face uncertainty in health as well. For example, Deb and Trivedi (1997, 2002) suggest that individuals with low health face higher health risk compared to others. While this potentially magnifies the results of Proposition 2, the total effect is again difficult to judge beforehand given the ambiguous effect of health on consumption utility and lifespan. Some insights on these concerns are gained in Section 5.3.

Despite the simplicity of the household model developed here, its implications seem both plausible and reasonably robust. This is also supported by theoretical claims of related literature

some anecdotal evidence for decreasing absolute prudence.

[8]While a temporal discount factor is common for multi-period models, it does not seem to be necessary for two-period models. In particular, the two models that inspired the model presented here – Delavande and Rohwedder (2011) and Elmendorf and Kimball (2000) – do not employ a temporal discount factor. Although it is not difficult to extend the model, there is thus also no apparent benefit. I opt for the simpler option as a result. Similar arguments hold for varying degrees of risk aversion, which can affect the magnitude but not the direction of the effect (given that all households are *not* risk-loving).

on income uncertainty, for example, Elmendorf and Kimball (2000), whose results are in line with those presented here. To investigate whether the theoretical claims on the effect of health care policy uncertainty can be supported by empirical analysis thus seems worthwhile.

3 Data

The considered data and the applied variable transformations are discussed in the following. After an overview of the household variables, Baker et al.'s (2016) health care policy uncertainty index is illustrated. The section concludes with summary statistics.

3.1 Household Data

The Health and Retirement Study (HRS) is a nationally representative panel that provides the most comprehensive and recent longitudinal data of Americans aged over 50. As emphasised by the vast literature using the HRS for analysis of precautionary savings and portfolio choice (e.g., Addoum, 2017; Goldman & Maestas, 2013; Poterba, 1994; Rosen & Wu, 2004), this is a particularly relevant sample of the US population due to its large share of total wealth and financial asset investment. The consumption and financial behaviour of sample households is thus likely to have broader macroeconomic implications. At the same time, since health is more of a concern to the elderly, the HRS dataset is relevant for studying the effects of health care policy uncertainty. As will be illustrated in some detail below, the survey collects detailed information on health status, wealth, and demographics of respondents.

I use all twelve waves (1992-2014; and 1993 and 1995 of AHEAD) of the HRS and the first seven waves (2001-2013) of its supplement, the Consumption and Activities Mail Survey (CAMS). This study relies on the RAND HRS Longitudinal File 2014 and the RAND HRS CAMS Spending Data 2015, which are more user-friendly versions of the core HRS with imputations for missing data. The files are merged with the Gateway to Global Ageing Harmonised HRS data for additional variables on households not included in RAND HRS[9].

For analysing households' financial behaviour, this study follows 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. The HRS also provides information on the latter's asset composition in the five most recent waves. However, because the empirical approach relies on temporal variation in health care policy uncertainty, omitting the previous eight waves is problematic. This study'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 (Love & Smith, 2010; Rosen & Wu, 2004)[10]. Further, shares of financial assets are calculated over total financial wealth rather than all assets, as non-liquid wealth (e.g,

[9]The HRS is sponsored by the National Institute on Ageing (grant number NIA U01AG009740) and is conducted by the University of Michigan. Citations of the Harmonised HRS, RAND CAMS, and RAND HRS are provided under (Health and Retirement Study, 2018a, 2018b, 2018c).

[10]Rosen and Wu (2004) also suggest approximating the share of stocks in IRAs using tabulations from the Survey of Consumer Finances (SCF). However, as this does not account for households' potentially heterogeneous reaction to uncertainty, attributing a fixed percentage of IRAs to the risky asset share would bias results on heterogeneous effects. In early results, I attributed 11% of IRAs to stocks on the basis of tabulations from the 2013 and 2016 SCFs for respondents aged over 50. Doing so did not affect the conclusions.

housing wealth) is not readily adjustable to changes in background risk (Goldman & Maestas, 2013). This study focuses primarily on the share of risky and safe assets as defined above, which seems reasonable as the IRA accounts do not allow for sufficiently detailed risk-classification and only a fraction of financial wealth is held in bonds.

Existing literature presents various approaches to defining households' savings. These include wealth accumulation across survey waves (e.g., Carroll, 1997), the ratio of wealth over permanent income (e.g., Lusardi, 1998), or the difference between income and consumption (e.g., Aaberge et al., 2017). These measures are not easily implemented for the HRS data, as a large share of households is retired with relatively low income from Social Security and pensions. Instead, this study exploits variance in households' consumption expenditures in line with Gruber and Yelowitz (1999) and Skinner (1988). In particular, I focus on households' spending during the previous year on durable goods, which includes household appliances such as TVs and kitchen equipment but excludes car purchases[11]. Durable consumption expenditures are particularly interesting, as previous research describes this category as more volatile and more reactive to economic downturns such as recessions (Attanasio, 1999; Crossley et al., 2013). Therefore, it seems that most evident effects could be expected in durable spending.

To adequately assess potential heterogeneity in the effect of health care policy uncertainty conditional on households' health, a suitable measure of health status is needed. Empirically, health is an intrinsically unobserved variable and a variety of proxies has been suggested in previous research (Currie & Madrian, 1999). Many studies assess health using survey respondents' answer to a question of the form "Would you say your health in general is (1) excellent, (2) very good, (3) good, (4) fair, or (5) poor?" Subjective health measures such as the HRS' 5-point Likert scale variable have often been shown to be highly correlated with medically determined health status, and have thus been argued to be an excellent proxy for health (e.g., Ferraro, 1980; LaRue et al., 1979). Yet, some doubts remain about how severe potential reporting bias is, and whether this is confounded by, for example, wealth or income (Currie & Madrian, 1999). As an alternative, some look to more objective measures of health. Berkowitz and Qiu (2006) and Wu (2003) suggest exogenous health shocks given by severe health conditions reported between survey waves. These are defined by diabetes, lung disease, cancer or malignant tumor growth, stroke and heart problems[12]. A particularly thorough approach to measuring health is provided by Fan and Zhao (2009). In addition to the above health proxies, they suggest separate measures for physical function limitations, for history of heart attack or stroke, and for limitations on the ability to work. I follow their suggestions to capture health in the most comprehensive manner. The exception is that – although available – this study does not consider work limitations due to the otherwise substantial reduction in observations[13]. In particular, health is assessed by the HRS' categorical subjective health measure (denoted by $subj \in \{1, \dots, 5\}$), a count variable on

[11]The RAND HRS data does not report separate car purchases, but instead combines these in a 'transport spending' category including other forms of non-durable spending such as fuel and public transport. Early results with merged durable and transport spending lead to similar conclusions (although of higher magnitude), but this strategy was ultimately neglected due to difficulties in interpretation of the transport category.

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

[13]This does not seem to be a crucial restriction due to the flaws of this variable. For example, Lindeboom and Kerkhofs (2009) point to endogenous, state-dependent reporting bias in self-assessed work limitations.

the historical number of severe health conditions ($medH \in \{0, \dots, 5\}$), a count variable on the number of physical limitations ($phys \in \{0, \dots, 6\}$)[14], and a binary indicator for whether any heart attack or stroke has been suffered in the past ($shock \in \{0, 1\}$).

Additionally, two variables to assess health care coverage and service utilisation are constructed: a binary indicator whether the respondent has health insurance ($insur \in \{0, 1\}$), and a binary indicator whether any doctor or hospital visit has occurred since the previous survey ($util \in \{0, 1\}$). Conditional on the health variables, both measures indicate lower exposure to medical expenditure risk. In particular, better health care coverage is positively associated with higher health service utilisation due to lower service costs (Smith, 1999). While the indices are substantially simplified and cannot adequately reflect varying health insurance plans, a consideration of this issue similar to that of, for example, Edwards (2008) and Rosen and Wu (2004), seems to be preferred to no consideration as in much of the literature on the effects of health on portfolio choice (e.g., Berkowitz & Qiu, 2006; Love & Smith, 2010; Wu, 2003).

Two important data issues arise. The first is the varying household composition across the sample. The common solution is to divide the data into single and couple households (e.g., Berkowitz & Qiu, 2006; Love & Smith, 2010; Rosen & Wu, 2004; Wu, 2003). This seems to be preferred over merely accounting for household size as a control variable as in Fan and Zhao (2009), due to intuitively different consequences of health shocks between household types[15]. The second issue relates to the definition of health status for couple households. Rosen and Wu (2004) suggest considering the health of husband and wife separately, Atella et al. (2012) take the average of the health measures across spouses, and Christelis et al. (2010) entirely omit health status of non-respondents. An appealing compromise between these suggestions is given by Coile and Milligan (2009) and Love and Smith (2010), who characterise households on basis of the least healthy spouse. With the aim to identify an ill individual (rather than to accurately assess the household's comprehensive health), I follow their suggestion and define the health measures introduced above on the maximum value across spouses for couple households.

Apart from the main variables of interest, I compile a set of household-level control variables in line with previous literature. Similar to Rosen and Wu (2004) and others, household-level controls are given by five educational attainment dummies, ethnicity, whether any children are living, age, intra-wave wealth and income quantiles, and the number of years in retirement. Gender is also accounted for when analysing single households. For couple households, only the demographics of the respondent are accounted for. Additional control variables such as labour force status and spouse-demographics were considered, but were ultimately omitted from the analysis. While expansive control specifications are unproblematic for standard econometric analysis given the large sample size, estimation of the latent class model introduced in Section 4.2.1 is infeasible when too many parameters are considered simultaneously. Fortunately, the restriction does not seem particularly restrictive as the inclusion of the additional covariates did

[14] Specifically, the sum of the binary indicators whether the respondent has difficulties to (1) walk one block, (2) sit for 2 hours, (3) get up from a chair, (4) climb a flight of stairs, (5) stoop or kneel, or (6) lift and carry 10lbs. Respondents' answers "can't do" and "don't do" are converted to a positive response. The measure is similar to the HRS-measures 'ADLs' and 'IADLs', but is defined separately as these are missing for a large sample share.

[15] For example, couple and single households seem to follow systematically different investment strategies (Addoum, 2017), potentially due to differences in risk sharing (Mazzocco, 2004).

not have any substantive effect in the baseline fixed effect analysis.

In addition to deleting observations who miss one or more of the above variables, including households with no positive financial asset holding, a few special observations are omitted from the analysis. These include households with a durable spending of more than \$6,000 a year (\$4,000 for singles), more than \$1,000,000 in stocks (\$660,000 for singles), as well as households with an investment in stocks equal to or exceeding their total physical asset wealth (including housing wealth and others)[16]. Further, households with a single observation are omitted to ensure that the samples are identical across fixed effect and pooled models. This leaves a sample of 164,884 for the portfolio choice analysis. Because CAMS only includes a random subset of the HRS households, 22,480 observations are available for the investigation of precautionary savings[17]. Appendix B provides a table with the amount of deleted variables at each stage.

Summary statistics of household characteristics are presented in Table 1. Nominal financial values are converted to 2010 US dollars using the Consumer Price Index corresponding to the interview year[18]. Durable consumption expenditures and the risky asset share are substantially concentrated at the 0-threshold: 57% (71%) of couple (single) households do not record positive durable spending and 63% (76%) of couple (single) households do not record positive investment share in risky assets. In contrast, less than 3% of both types of households have a 0-share of safe assets, but 30% (49%) of couple (single) households have all their financial wealth in safe assets. Section 4 illustrates the necessary empirical considerations to address this issue.

3.2 Measuring Health Care Policy Uncertainty

Existing literature presents several measures of policy uncertainty, with much of the current work relying on subjective policy uncertainty (e.g., Delavande & Rohwedder, 2011; Luttmer & Samwick, 2018) or on uncertainty around elections and other significant political events (e.g., Aaberge et al., 2017; Agarwal et al., 2018; Giavazzi & McMahon, 2012). Recently, Baker et al. (2016) take an alternative approach and develop a computer-driven, news-based policy uncertainty index. It is based on the number of occurrences of articles with word triplets "uncertain", "economic", and "policy" (and their synonyms) of ten major newspapers in the US. The 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 on the effect of policy uncertainty on firms (e.g., Bloom, 2014) or on macroeconomic tendencies (e.g., Stock & Watson, 2012). To the best of my knowledge, this paper is just the second to apply Baker et al.'s (2016) policy uncertainty indices in a study of households, preceded only by Gábor-Tóth and Georgarakos's (2018) ongoing work.

[16] The omitted observations represent the upper, most outer tails of the sample distribution for durable consumption and stock investment. While they do not affect the results of the baseline fixed effect analysis, their inclusion leads to component problems in the latent class Tobit model introduced in Section 4.2.1. The model seems to identify 'outlier' components that constitute of these very few observations. In this case, the corresponding coefficients do not seem to be identifiable due to the excess of parameters relative to component-observations.

[17] The panel is unbalanced – that is, many households are not participating in all survey waves. Fortunately, a balanced sample is not required as the identification approach is based on correlating the cross-section and inter-temporal variation of consumption/financial asset shares with inter-temporal variation of health care policy uncertainty. Further, there is no evidence to suggest that surviving households react more strongly to health care policy uncertainty shocks (in line with Love and Smith's (2010) claim in the context of health shocks).

[18] The corresponding data citation is provided under United States Bureau of Labor Statistics (2018).

Fortunately, Baker et al. (2016) developed not only a general economic policy uncertainty index but also several categorical indices. Among them a health care policy uncertainty index, which is based on the frequency of articles featuring the above word triplet as well as one term related to health care such as "Medicaid", "health insurance" or "Obamacare"[19]. Figure 1 shows the health care policy uncertainty index between 1992 and 2017, and its average over the preceding 12 months. The latter is characterised by three substantive increases that can be linked to health care reform 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. I merge the household data with the 12-month average preceding the end date of the HRS interview. The CAMS survey predates the HRS interviews by several months, but unfortunately, the specific survey month is unknown. As a suitable approximation, each household is matched to the 12-month average preceding October of the respective year. This is reasonable as all consumption data is collected between September and December.

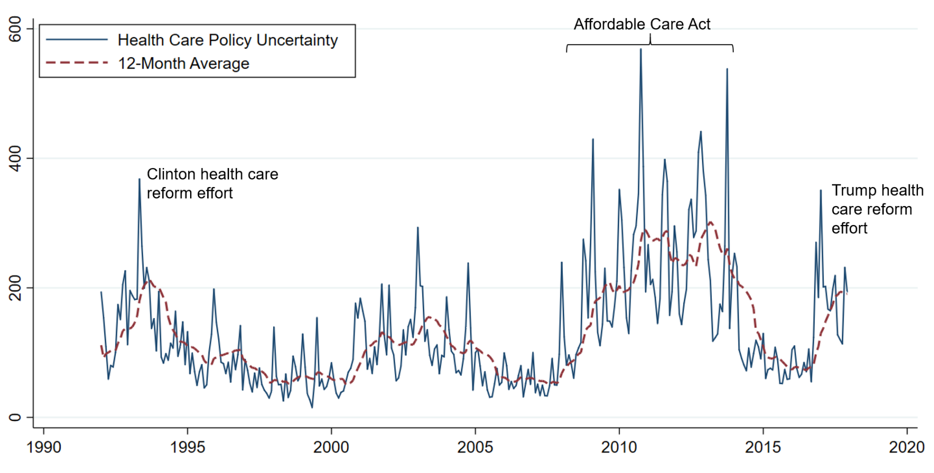


Figure 1: Health Care Policy Uncertainty Index 1992 - 2017
The index reflects the scaled monthly number of newspaper articles containing the word-triplet "uncertain", "economic", and "policy" (and their synonyms) and one term on health care (e.g., "health insurance"). It is calculated on basis of the Access World News newspaper archive with about 1,500 US papers, normalised to a mean of 100 from 1985 to 2010. The dashed line is the index's average based on the preceding 12 months.

Finally, additional macroeconomic uncertainty measures are merged with the data to address endogeneity concerns and confirm the robustness of the results. In particular, I follow Gábor-Tóth and Georgarakos (2018) and consider both the 12-month average of the S&P 500 Index growth rate and the Implied Volatility Index (VIX) to account for the first and second moment of financial returns[20]. To capture general economic uncertainty, the 12-month growth rate average of the Conference Board's Coincident Indicator is also included in all specifications. The measure is a weighted average of different macroeconomic variables that typically move in synchronisation with the business cycle (e.g., the industrial production index). As such, it not only moves strongly pro-cyclically but also smooths out some of the fluctuations of the individual

[19] 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." A reference of the index is provided under Baker et al. (2018).

[20] Both measures are price adjusted for both dividends and splits at closing. The indices are taken from Yahoo Finance (2018a, 2018b), with corresponding data citations in the references.

variables. These features allow researchers to better account for business cycles than individual macroeconomic series would (The Conference Board, 2001)[21]. Additional controls including NBER's recession indicator, the Conference Board's Leading Economic Indicator, and Baker et al.'s (2016) fiscal policy uncertainty index were also tested, but are ultimately omitted to keep the coefficient vector concise for reasons discussed above. Their omission seems appropriate as none of the additional regressions indicated any effects on the conclusions.

Sample summary statistics of the macroeconomic variables are provided in Table 1.

Table 1: Summary Statistics

	Mean	Sd.		Mean	Sd.		Mean	Sd.
Dependent			*Hh Proportions (%)*			*Hh Characteristics*		
Durable spend. ($)	351.370	706.268	Female	0.576	0.494	*subj*	3.076	1.047
Risky assets (%)	0.144	0.269	Any children	0.930	0.255	*medH*	0.894	0.928
Safe assets (%)	0.600	0.406	Retired	0.516	0.500	*phys*	2.320	1.990
IRA (%)	0.240	0.339	No high school	0.184	0.387	*shock*	0.173	0.378
Bonds (%)	0.016	0.085	GED	0.044	0.204	*util*	0.973	0.163
Macro. Controls			High school	0.328	0.469	*insur*	0.778	0.416
HPU	120.650	93.116	Some college	0.229	0.420	Income ($)	0.729	1.503
HPU_{12}	125.635	69.306	Above college	0.216	0.412	Wealth ($)	3.842	10.032
VIX_{12}	19.352	4.917	Caucasian	0.855	0.352	Years ret.	6.627	9.569
$SP500_{12}$	0.009	0.012	African Am.	0.108	0.311	Age	66.587	11.093
CEI_{12}	0.002	0.001	Other ethn.	0.036	0.187			

Statistics are based on the sample of 164,884 observations, except for durable spending where the CAMS sub-sample of 22,480 observations is used. 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. Health variables of couple households are defined as the maximum of the spouses. Other individual-specific household characteristics are defined on the survey-respondent. *Italics* denote coded variables defined in Section 3.1. $ denotes 2010 Dollars. Wealth and Income are in $100,000. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages.

4 Methodology

This section describes the empirical approach to analyse the effect of health care policy uncertainty on households' consumption and portfolio choice. Following Honoré's (1992) censored fixed effect model, the two heterogeneous effect models – a concomitant-variable latent class Tobit model and an adaptation of Zeileis et al.'s (2008) model-based recursive partitioning – are introduced. Throughout, I focus on the model specifications and their interpretation. Further considerations, for example on the specific EM algorithm, are illustrated in Appendix C.

4.1 Censored Fixed Effect Model

As noted in Section 3.1, households' consumption and risky asset share are concentrated at the 0-threshold and the safe asset share is concentrated at 1[22]. This asymmetric nature of outcome variables renders standard linear regression estimation unsuitable. While the issue seems to be largely neglected in studies on policy uncertainty's effect on households[23], previous research on portfolio choice provides some guidance on useful techniques. A common solution

[21] The corresponding data citation is provided under The Conference Board (2018).

[22] While both the risky asset share and the safe asset share are also bounded by 1 and 0, respectively, no substantial clustering occurs (less than 1% for risky assets, and less than 3% for safe assets). Following existing literature, I thus consider a one-sided censored regression model.

[23] For example, Aaberge et al.'s (2017) consumption measures are likely to be substantially concentrated at 0.

seems to be a Tobit model (e.g., Cardak & Wilkins, 2009; Wu, 2003), with some examples of random effects extensions (e.g., Berkowitz & Qiu, 2006; Rosen & Wu, 2004). However, as Fan and Zhao (2009) and Love and Smith (2010) note, the consistency of these results depends crucially on the assumption that the unobserved heterogeneity is uncorrelated with covariates. As this is likely violated, researchers would instead turn to a fixed effects model. Unfortunately, coefficient estimates of a fixed effects Tobit model optimised via maximum likelihood are inconsistent due to the 'Incidental Parameter Problem' (Greene, 2004; Honoré, 1992).

A suitable alternative is suggested by Honoré (1992), who develops a semiparametric censored fixed effects estimator. Consider a model censored at 0 of the form

$$y_{it} = \max\{0, \beta_{i0} + X_{it}\beta_1 + \varepsilon_{it}\}, \tag{3}$$

where $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$ denote the household and time period, respectively, y_{it} is the censored outcome variable, X_{it} is a set of covariates with corresponding coefficient vector β_1, β_{i0} is the household-fixed effect, and ε_{it} is the error term. Honoré (1992) derives a two-period panel estimator and notes it can be extended in a straightforward manner to a multi-period panel setting by taking into account all time period pairs. In particular, if the pair $(\varepsilon_{it}, \varepsilon_{is})$ is identically distributed as the pair $(\varepsilon_{is}, \varepsilon_{it})$ conditional on $(X_{it}, X_{is}, \beta_{i0})$ for $t, s \in \{1, \ldots, T\}$, then β_1 can be estimated by

$$\begin{aligned} \hat{\beta}_1 = \arg\min_b \sum_{i=1}^{N} \Bigg(\sum_{t=1}^{T} \sum_{s=t+1}^{T} \Bigg(&(\max\{y_{it}, \Delta X_i b\} - \max\{y_{is}, -\Delta X_i b\} - \Delta X_i b)^2 \\ &+ 2I[y_{it} < \Delta X_i b](\Delta X_i b - y_{it}) y_{is} + 2I[y_{is} < -\Delta_i b](-\Delta X_i b - y_{is}) y_{it} \Bigg) \Bigg), \end{aligned} \tag{4}$$

where $\Delta X_i = X_{it} - X_{is}$ and I is an indicator function.

The estimator is consistent as $N \to \infty$ rather than $T \to \infty$ as in the maximum-likelihood case (Stephens, 2002). Asymptotic standard errors are computed using the first order condition of equation (4). While notation corresponds to a balanced panel for brevity, the estimator is also suitable for unbalanced panels (Honoré, 2002; Love & Smith, 2010). The model does not require a parametric specification of the error distribution, however, pairwise exchangeability conditional on the explanatory variables is required. In other words, while errors are potentially heteroskedastic across households, they are assumed to be uncorrelated over time. The latter is often not satisfied in panel data[24], yet, no suitable and consistent estimator of censored regression models seems to exist where this is not a required assumption[25]. For anecdotal evidence that this is not a major concern for the data at hand, I compare conventional standard errors with household-level clustered standard errors of the linear fixed effect model and find no substantive differences (see Appendix C.1 for results). While not without qualifications, Honoré (1992) thus seems to provide the most suitable model for this study.

Unlike in a linear regression model, the resulting estimates cannot readily be interpreted as

[24]Bertrand et al. (2004) show that the neglect of error-correlation in linear panel models leads to misspecified standard errors in many empirical studies.

[25]Hochguertel (2003) uses a Tobit model with a parametric variance specification, however, this seems infeasible for this study due to the large number of coefficients in case of the latent class model introduced in Section 4.2.1.

marginal effects. Recall that for a standard Tobit model, marginal effects would be given by

$$\frac{\partial E[y_{it}|X_{it},\beta_{i0},\beta_1]}{\partial x_{k,it}} = \left(1 - \Phi\Big(-\frac{\beta_{i0}+X_{it}\beta_1}{\sigma}\Big)\right)\beta_{1k}, \tag{5}$$

where the term in parentheses is the household's probability of a positive y_{it}, and β_{1k} denotes the coefficient corresponding to the kth covariate in X_{it}. Because β_{i0} is 'differenced-out' by Honoré's (1992) estimator, the magnitude of the marginal effects cannot be calculated[26]. While Honoré (2002) notes that β_1 nevertheless captures the marginal effect of covariates on the underlying latent variable y^*, this interpretation is not particularly relevant when interested in spending and investment reductions. Due to this complication, Hochguertel (2003) and Love and Smith (2010) use Honoré's (1992) estimator along a Tobit model; the former acting as a robustness check on the easier interpretable results of the latter. This study follows the same approach.

In summary: to empirically test Proposition 1 – health care policy uncertainty negatively affects household consumption and relative demand for risky assets – I regress households' durable expenditures, and risky and safe asset shares on the log-transformed 12-month health care policy uncertainty average and a set of controls as introduced in Section 3, using both Honoré's (1992) censored fixed effect model as well as a pooled Tobit model[27,28]. For simplicity, the share of safe assets is converted to the share of non-safe assets in estimation. Coefficients can be re-adjusted by simple sign-reversal. The economic and statistical significance of the health care policy uncertainty coefficients is used to evaluate the theoretical claims.

4.2 Heterogeneous Effects

The censored fixed effect model of the previous section controls for time-varying household-level controls, time-invariant unobserved heterogeneity, and potentially confounding economic uncertainty using various macro-level controls. Similarly careful empirical specifications are often said to allow for causal inference (e.g., Aaberge et al., 2017; Baker et al., 2016; Giavazzi & McMahon, 2012). To further strengthen the claim that the estimates capture a causal effect of health care policy uncertainty on households' consumption and portfolio choice, I proceed by considering Proposition 2 – bad health magnifies the effect of health care policy uncertainty.

This strategy is similar to that of, for example, Baker et al. (2016), who argue that firms with higher dependency on government contracts should be more affected by policy uncertainty, or Giavazzi and McMahon (2012), who make a similar claim about non-civil servants in Germany. However, for this approach to contribute to the story of causal effects, it is crucial that policy uncertainty exposure is unconfounded with exposure to other forms of uncertainty. Non-civil servants in Germany, for example, are also much less affected by business cycles, which raises doubts as to whether the policy uncertainty estimates are spurious. Compared to previous studies' strategies, variation in households' health seems to be a particularly suitable measure to capture uncertainty exposure across households. As illustrated in Section 2.1, health is likely

[26] Note, the sign of the marginal effect and β_{1k} are equal as $\Phi(\cdot) \in [0,1]$, also for Honoré's (1992) estimator.

[27] A random effects Tobit model as in Rosen and Wu (2004) could also be considered. However, the pooled model leads to consistent estimates of the slope parameters in a random effects model as the effects are additive (Cameron & Trivedi, 2005). Without apparent benefit, this study thus opts for the simpler model.

[28] Honoré's (1992) estimator is implemented using the Stata code available at his website: `https://www.princeton.edu/~honore/stata/`.

to have a magnifying effect on the impact of health care policy uncertainty, and existing literature does not provide evidence that health affects households' response to, for example, economic downturns. While it is potentially concerning that health insurance in the US is often linked to employment, a large share of the sample is retired and is thus not at risk of being more exposed to medical expenditure risk due to potential job loss. Further, as illustrated by Smith (1999), health shocks will not substantially alter labour supply during retirement, and income from Social Security and pensions will remain fixed. As a result, health of older Americans is unlikely to affect their responsiveness to economic uncertainty. Remaining doubts are addressed by controlling for measures of economic uncertainty as before.

The empirical approach of the existing policy uncertainty literature for analysing heterogeneity in causal effects is restricted to a multiplicative-interaction specification of the form

$$y_{it} = \beta_{i0} + \beta_1 PU_t + \beta_2 PU_t z_{it} + X_{it}\beta_3 + \varepsilon_{it}, \tag{6}$$

for $i \in \{1, \dots, N\}$ and $t \in \{1, \dots, T\}$, where PU_i is the policy uncertainty measure at time t, z_{it} is the exposure variation measure of individual i at time t, and X_{it} are control variables with $z_{it} \in X_{it}$ (e.g., Baker et al., 2016; Giavazzi & McMahon, 2012). While this functional form allows for a simple interpretation of β_2, it comes with some crucial caveats. Most importantly, the multiplicative-interaction model restricts parameter heterogeneity to be of a pre-specified additive form. This is particularly problematic when heterogeneity is expected to stem from complex characteristics such as health, where an array of potential variables is available and it is unclear a priori which combinations, interactions and transformations are most appropriate. Because of the numberless possible variations, it is difficult to motivate this approach against the concerns raised by Hainmueller et al. (2018), who show that a substantial share of heterogeneous treatment effect results in top economic journals seems to be highly model dependent[29].

To address these qualifications, this study considers two alternatives for identifying heterogeneous effects: a concomitant-variable latent class Tobit model and an adaptation of Zeileis et al.'s (2008) model-based recursive partitioning procedure. As neither model requires the pre-specification of the heterogeneous effect form, both are well suited to analyse possible variation in the effect of health care policy uncertainty with respect to the six health and health care measures. Further, both models allow approximation of possible non-linearities in the effect of health care policy uncertainty by segmenting the population into homogeneous sub-populations with distinct coefficients. Despite their similarities, however, each has considerable advantages. As Frick et al. (2014) discuss, latent class models can detect sub-populations when effects are substantially heterogeneous, even when there is only a weak (or no) association between coefficient differences and observed variables. In contrast, the model-based recursive partitioning method requires strong association of sub-populations with observed covariates, but is able to identify parameter heterogeneity in much more detail when this is the case. Because existing literature provides ambiguous suggestions about the extent of association of potential sub-populations and observed health variables[30], it is optimal to consider both approaches.

[29]This caveat is in addition to identification issues when time-fixed effects are used in multiplicative interaction models as in Baker et al. (2016). See Appendix C.2 for an illustration of such a pitfall.

[30]As illustrated in Section 3.1, existing literature finds observed health variables to be highly correlated with

Unfortunately, Honoré's (1992) censored fixed effect model cannot be employed for either the latent class model or the model-based recursive partitioning procedure for two reasons. First, its solution has turned out to be highly computationally intensive. As both heterogeneous effect models require plentiful re-estimation, the necessary computational time of either exceeds many days. Second, and more importantly, Honoré's (1992) estimator does not permit the calculation of likelihood values as the household-fixed effects are 'differenced-out'. As illustrated below, these are essential for the calculation of the posterior component-specific likelihoods of the latent class model as well as the split-criterion of the model-based recursive partitioning. For the advanced investigations into heterogeneous effects, I thus reconsider the pooled Tobit model without fixed effects. At least to some degree, however, the fact that the sample is split into sub-populations corrects for some unobserved heterogeneity across households.

In the following two subsections, the concomitant-variable latent class Tobit model and the Tobit model-based recursive partition procedure are illustrated with particular focus on their respective contributions to analysing heterogeneity in the effect of health care policy uncertainty.

4.2.1 Concomitant-Variable Latent Class Tobit Model

Latent class models were first introduced to health economics by Deb and Trivedi (1997), and have since been established as important tools for analysing heterogeneous health care demand (Bago d'Uva, 2006; Deb & Trivedi, 2002). As an advantage over conventional models, they do not require a fixed distinction between households based on observed variables. Instead, latent class models allow the coefficient-heterogeneity to stem from unobserved characteristics such as a households' lifestyle, attitudes to health risk, and long-term health. While the observed health variables might be important determinants of the latter, Deb and Trivedi (1997, 2002) suggest that such proxies may not fully capture heterogeneity from this source. As households who might be characterised as healthy based on the observed variables might nevertheless react strongly to health care policy uncertainty due to, for example, health risk attitude, a latent class model seems particularly tenable for analysing potential heterogeneity[31]. A particularly appealing variant is the concomitant-variable latent class model developed by Dayton and Macready (1988). In addition to identifying latent subpopulations and estimating an econometric model within each segment, it also allows for simultaneous estimation of the association between class-membership and observed variables. It has proven valuable in the characterisation of heterogeneous consumer groups in marketing research (e.g., Kamakura et al., 1994), and thus seems to be a promising method for analysing whether the observed health measures are associated with the heterogeneity in the effect of health care policy uncertainty.

In contrast to the standard assumption of one underlying econometric model, a latent class model considers the possibility that the data consists of several unobserved segments, each with similar distributional form but with heterogeneous parameters (Aitkin & Rubin, 1985).

households' health. However, Deb and Trivedi (1997, 2002) suggest that health care utilisation-caused expenditures largely depend on unobserved heterogeneity (and propose a latent class model as a consequence).

[31] From an econometric perspectives, latent class models also alleviate concerns about potentially misspecified underlying probability densities. Being more flexible than standard regression models, they can serve as a better approximation to any unknown probability density (Laird, 1978). These features have also motivated the application latent class models in fields with similar aims to uncover population heterogeneity as this study, for example, marketing research (e.g., Kamakura & Russell, 1989; Wedel et al., 1993).

Following the latent class interpretation of mixture models (e.g., McLachlan & Peel, 2004), an M-component latent class model can be written as

$$y_{it} = \begin{cases} f(y_{it}|X_{it}, \theta_1), & \text{if } S_{it} = 1 \\ \vdots \\ f(y_{it}|X_{it}, \theta_M), & \text{if } S_{it} = M \end{cases} \tag{7}$$

for $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$, where y_{it} is the outcome variable with component-specific densities $f(\cdot|X_{it}, \theta_s)$ with X_{it} being a variable vector and θ_s being the component-specific coefficient vector[32]. $S_{it} = s$ indicates that observation (it) originates from subpopulation s. Although the component labels are unobserved, it is possible to estimate the model by considering S_{it} as realisations of the discrete random variable $\tilde{S}$ with corresponding probabilities $P[\tilde{S}_{it} = s] = \pi_{s,it}$ that satisfy $\sum_{s=1}^{M} \pi_{s,it} = 1$. The resulting likelihood function is given by

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{N} \prod_{t=1}^{T} \Big(\sum_{s=1}^{M} \pi_{s,it} f(y_{it}|X_{it}, \theta_s) \Big), \tag{8}$$

where $\boldsymbol{\theta}$ summarises the component specific coefficients. To account for the asymmetry of the outcome variables, the mixture densities, $f(y_{it}|X_{it}, \theta_s)$, are pooled Tobit densities given by

$$f(y_{it}|X_{it}, \theta_s) = \left(\Phi\Big(\frac{-X_{it}\beta_s}{\sigma_s} \Big) \right)^{I[y_{it}=0]} \left(\frac{1}{\sigma_s \sqrt{2\pi}} \exp\Big(\frac{-1}{2\sigma_s^2} \big(y_{it} - X_{it}\beta_s \big)^2 \Big) \right)^{I[y_{it}>0]}, \tag{9}$$

for $s \in \{1, \ldots, M\}$, $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$, where Φ denotes the normal CDF. For ease of notation, θ_s summarises the parameters β_s and σ_s.

Apart from identifying potentially heterogeneous θs and the underlying sub-populations, the *concomitant-variable* latent class model also allows for inferences on the association between households' health measures and their component-membership. First, instead of merely modelling the *prior* probability of belonging to a component as an invariant proportion (e.g., Deb & Trivedi, 1997), it is possible to model the random variable $\tilde{S}$ by a multinomial logit model as suggest in (Dayton & Macready, 1988). Here, 'prior' highlights that y_{it} has not been observed yet. Considering the prior probability of belonging to component s, this results in

$$\pi_{s,it} = P[S_{it} = s|Z_{it}] = \frac{\exp\big(\alpha_{s,0} + Z_{it}\alpha_{s,1}\big)}{\sum_{j=1}^{M} \exp\big(\alpha_{j,0} + Z_{it}\alpha_{j,1}\big)}, \tag{10}$$

for $s \in \{1, \ldots, M\}$, $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$, where Z_{it} is a vector of concomitant variables with corresponding coefficient vector α_1. The coefficients of component 1 are set to 0 for identification purposes (i.e., $\alpha_{1,0} = 0$ and $\alpha_{1,1} = 0$). Taking Z_{it} to be the household health variables, one can make inferences on the characteristics of the subgroups by examining their partial effects on the prior probability. In a two-component mixture, for example, a positive and significant coefficient $\alpha_{2,1k}$ indicates that households with higher $z_{k,it}$ have a higher probability

[32] It is now also clear that variable restrictions are particularly important in a mixture model setting: each added covariate requires estimation of M additional coefficients.

of belonging to the second component with component-specific coefficients θ_2. Empirical evidence for Proposition 2 is found, if estimation results in a higher health care policy uncertainty coefficient corresponding to the component with higher prior probabilities of 'ill' households.

Second, it is possible to calculate an observation's *posterior* probability of stemming from the mixture component s – that is, the probability of belonging to a particular component *after* having observed y_{it}. This can be calculated in a Bayesian fashion by

$$\tau_{s,it} = P[S_{it} = s|y_{it}, X_{it}, Z_{it}, \boldsymbol{\theta}] = \frac{\pi_{s,it} f(y_{it}|X_{it}, \theta_s)}{\sum_{j=1}^{M} \pi_{j,it} f(y_{it}|X_{it}, \theta_j)}, \tag{11}$$

for $s \in \{1, \ldots, M\}$, $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$. See, for example, McLachlan and Peel (2004). In contrast to the prior probabilities, this does not allow for statistical tests on the association between components and features Z_{it} in a straightforward manner without disregarding the uncertainty in determining $\pi_{s,it}$ and θ_s (Kamakura et al., 1994). Nevertheless, the posterior probabilities enable the characterisation of 'typical' component-observations through calculation of the component-specific means. For any variable $z_{k,it}$, this is given by

$$\bar{z}_k^s = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \tau_{s,it} z_{k,it}}{\sum_{i=1}^{N} \sum_{t=1}^{T} \tau_{s,it}}, \text{ for } s \in \{1, \ldots, M\}. \tag{12}$$

The component-specific means are particularly useful if no significant association between health variables and components is found, as suggested by Deb and Trivedi (1997, 2002). If the component with the higher health care policy uncertainty coefficient is characterised as 'ill' on basis of the component-specific means, this would provide empirical support for Proposition 2.

An important issue of latent class models is the number of components, M. When economic theory provides little guidance, researchers cannot rely on likelihood ratio tests as models are not necessarily nested, but instead have to use penalised likelihood criteria such as the AIC or BIC to determine an appropriate number of mixture components (McLachlan & Peel, 2004). Fortunately, existing literature provides some insights. As suggested by Deb and Trivedi (1997, 2002), who analyse heterogeneous demand for health care services, it seems sensible to assume two underlying subpopulations; one potentially characterised by 'healthy' households, the other by 'ill' households. Therefore, I will adopt a two-component latent class model[33].

Because the logarithm of the likelihood in (8) contains a log of a sum due to the mixture-term, maximum likelihood estimation of latent class models is numerically difficult. As an alternative, I estimate the concomitant-variable latent class Tobit model using a modified version of the relevant EM algorithm developed by Karlsson and Laitila (2014) and Van der Heijden et al. (1996). For robust standard errors, this study relies on the panel bootstrap standard error estimate as illustrated by Cameron and Trivedi (2005) for standard panel models. To allow for bootstrapping standard errors despite the label switching problem of latent class models, the

[33] As a precaution, I also estimated three-component latent class models. While no improvement was found for durable consumption and risky assets, the information criteria indicated a better fit for safe assets. However, in all cases, the additional sub-population seems to stem from a split of the smaller, health care policy uncertainty-*un*responsive component. The results neither allowed for more detailed conclusions, nor did the additional component have an impact on any conclusions from the two-component model. The restriction thus seems well justified, not only based on previous literature's suggestions but also from an econometric perspective.

coefficient vectors are ordered by the component-specific variance in each bootstrap iteration as suggested by McLachlan and Peel (2004). The algorithm is implemented in R, with code readily available upon request. Appendix C.3 provides an outline of the estimation procedure.

4.2.2 Tobit Model-Based Recursive Partitioning

The latent class Tobit model is a substantial improvement over an a priori-specified heterogeneous effects models such as the multiplicative-interaction model, yet, the model is not free of qualifications itself. Apart from assessing differences between a few sub-populations, for example, more detailed conclusions could be drawn if a higher number of potential segments is considered. While this is difficult with a latent class model as the number of components requires pre-specification by the researcher, recent developments in the interdisciplinary literature on machine learning in economics provide new appealing techniques that address such limitations (Athey, 2017, 2018; Mullainathan & Spiess, 2017). Of particular interest to this study are the developments of partitioning methods (e.g., regression trees) to the topic of heterogeneous causal effects (e.g., Athey & Imbens, 2015, 2017). These methods are useful as they can model non-linear, highly interactive heterogeneous treatment effects while nevertheless allowing for statistical inference on the causal structures in a visually intuitive manner. Unfortunately, however, the majority of existing literature on economic applications of machine learning has solely considered the case of binary treatment effects under ideal data conditions (i.e., no censoring/asymmetry). These qualifications render existing methods in economics – among them the causal trees proposed by Athey and Imbens (2015) or the causal forests proposed by Wager and Athey (2018) – unsuitable for applications with continuous parameters of interest and/or with asymmetric, censored outcome variables. This study therefore requires a novel approach.

A machine learning technique on heterogeneous causal effects that is yet to be explored in economics is Zeileis et al.'s (2008) model-based recursive partitioning approach. Developed originally for linear and logistic regression, the procedure was extended to psychometric models (e.g., Strobl et al., 2015, 2011) as well as generalised linear models and maximum likelihood models (Rusch & Zeileis, 2013). I adapt the method to asymmetric outcome variables by employing a Tobit model in each partition and to a setting with observed nuisance parameters.

For ease of comparison, the model can be written similarly to the latent class specification of equation (7). In particular, consider the G-partition model given by

$$y_{it} = \begin{cases} f(y_{it}|X_{it}, \theta_1), & \text{if } \{Z_{it}\} \in \mathcal{Z}_1 \\ \vdots & \\ f(y_{it}|X_{it}, \theta_G), & \text{if } \{Z_{it}\} \in \mathcal{Z}_G \end{cases} \tag{13}$$

where a particular observation stems from the gth partition if its features, $\{Z_{it}\}$, are element of the partition's feature-space, $\mathcal{Z}_g = \mathcal{Z}_{g,1} \times \ldots \times \mathcal{Z}_{g,B}$, with B being the number of features. As before, $f(\cdot|X_{it}, \theta_g)$ denotes the density of a pooled Tobit model given in equation (9). An important distinction to the latent class model is that the procedure considers an observation's partition-membership to be entirely determined by its feature vector Z_{it}. While thus not permitting the parameter heterogeneity to partly stem from latent characteristics, Tobit model-based recursive partitioning can approximate highly non-linear and interactive heterogeneous effect-forms. If the parameter differences are strongly associated with the observed health measures, this allows for a level of detail in inferences on the underlying data structures that is unmatched by alternative methods. As estimating the model (13) with conventional techniques is infeasible, Zeileis et al. (2008) propose a greedy, forward-searching algorithm for unbiased estimation of the partition-specific parameters θ_g and associated feature-spaces $\mathcal{Z}_g$. In essence, model-based recursive partitioning estimates the G-partition model by (1) fitting the local model $f(\cdot)$ to the data through minimisation of the objective function Ψ, (2) testing for parameter instability over the set of features Z and selecting the feature associated with the highest instability z_k^*, (3) computing the split point of z_k^* that locally optimises Ψ, and (4) split the data into two daughter partitions and repeat the procedure. Steps (1)-(3) are discussed in some detail below.

Step (1), fitting the local model, simply estimates a pooled Tobit model through minimisation of its negative log-likelihood (i.e., sum of the log-transformed Tobit densities over all observations). Following Zeileis et al. (2008), this objective function is denoted by Ψ. A relevant side product of this step are each observation's score function contribution: $\psi_{it} = \frac{\partial \Psi(y_{it}, X_{it}, \theta)}{\partial \theta}$.

Step (2), testing for parameter instability, assesses whether a sample split with respect to one feature captures potential instability of the Tobit model coefficients. For this purpose, the authors suggest testing whether ψ_{it} fluctuate randomly around their mean 0 or exhibit systematic deviations over a particular feature. Zeileis et al. (2008) only explicitly consider testing for parameter instability of the entire parameter space. This is problematic as splits could stem from instability of nuisance parameters instead of coefficients of interest. Fortunately, this concern is easily alleviated as the method can be adjusted to test for instability on only a subset of θ in a straightforward manner; instead of ψ_{it}, one can consider $\psi_{it}^j = \frac{\partial \Psi(y_{it}, X_{it}, \theta)}{\partial \theta_j}$. Systematic deviations from 0 can then be captured by the empirical fluctuation process

$$W_k(l) = \frac{1}{\hat{\sigma}(\theta_j)\sqrt{n}} \sum_{i=1}^{\lfloor nl \rfloor} \hat{\psi}^j_{\eta(z_{j,i})} \qquad (0 \leq l \leq 1), \tag{14}$$

where $\hat{\sigma}(\theta_j)$ and $\hat{\psi}^j$ are the estimated standard error and the estimated score contribution of the coefficient of interest θ_j, n is the number of observations at the current partition, and $\eta(z_{k,i})$ denotes the ordering permutation with respect to the kth feature. Put simply, $W_k(l)$ is the partial sum process of the score contributions ordered by the feature variable, scaled by the number of observations and a suitable standard error estimate.

To assess instability over ordered discrete variables, the authors suggest the test statistic

$$\lambda_{\chi^2}(W_k) = \sum_{c=1}^{C} \frac{1}{n|I_c|} \left|\left| \Delta_{I_c} W_k\left(\frac{i}{n}\right) \right|\right|_2^2, \tag{15}$$

where $\Delta_{I_c} W_k\left(\frac{i}{n}\right)$ is the increment of the empirical fluctuation process over the observations of category $c \in \{1, \ldots, C\}$ of the kth feature (with associated indices I_c) – that is, the sum of score contributions of category c. The statistic is then given by the weighted sum of the squared L_2 norm of the increments with asymptotic distribution $\chi^2(C-1)$ (Zeileis & Hornik, 2007; Zeileis et al., 2008). A substantial advantage of this parameter instability test is that the coefficients and corresponding score contributions only have to be calculated once in each partition. To test for instability across multiple features, the scores merely have to be reordered. The null hypothesis of stability is rejected in the current partition whenever the minimal p-value corresponding to any feature falls below a preimposed significance threshold[34]. If multiple tests reject stability, the sample is split with respect to the feature with the lowest p-value.

Step (3), finding a suitable threshold to split the sample along the feature z_k^*, is trivial. For a binary split at each node, two rivalling partitions can be compared in a straightforward manner by comparing the segmented objective function $\sum_{b=1}^{2} \sum_{i \in I_b} \Psi(y_{it}, X_{it}, \theta_b)$. The optimal cut-off is then determined by performing an exhaustive search over all possible partitions.

Splitting the sample according to step (3) concludes one iteration of the model-based recursive partitioning algorithm. The procedure is continued until no further parameter instability is found in any nodes or when no further splits are feasible due to sub-sample size. Contrasting the latent class model, no prior choice on the number of partitions, G, is required. I implement the Tobit model-based recursive partitioning procedure in R using Hothorn and Zeileis's (2015) library that allows for flexible algorithm building. Standard errors suggested by Zeileis et al. (2008) are the standard errors of the Tobit models in each partition. Although these are uncorrected for the uncertainty in the estimation of partitions' feature spaces, no correction has yet been developed. Thus the uncorrected standard errors are considered despite this caveat.

Using the Tobit model-based recursive partitioning method, I analyse whether parameter instability in the health care policy uncertainty coefficient can be captured by splitting along the health and health care measures. Resulting estimates provide valuable empirical insights that allow evaluation of Proposition 2. In particular, to assess whether households with worse health are more affected by health care policy uncertainty, the coefficient estimates corresponding to 'healthy' and 'ill' sample partitions should be compared. As will become clear in Section 5.3, the sample division of the model-based recursive portioning allows for inferences on the parameter heterogeneity that exceed a mere binary split in much detail.

5 Results

This section applies the models of the previous section to analyse the effect of health care policy uncertainty on households' consumption and financial behaviour. After testing for an effect of health care policy uncertainty using the fixed effect and pooled Tobit models (Proposition 1), the concomitant-variable latent class Tobit model and the Tobit model-based recursive partitioning procedure are applied to analyse whether potential heterogeneity in effect of health care policy uncertainty is associated with households' health (Proposition 2).

5.1 Censored Fixed Effect Model

The purpose of the baseline Tobit regressions is to test Proposition 1 – whether increased health care policy uncertainty causes a decrease in households' consumption and relative demand for risky assets. Table 2 presents the results of the censored fixed effect and pooled Tobit models. For brevity, only the coefficient corresponding to the log of the 12-month health care policy

[34] As concerns on multiple hypothesis testing arise, Bonferroni-adjusted p-values are considered.

uncertainty average is included. Complete estimation results can be found in Appendix D.1.

Table 2: Fixed Effect and Pooled Tobit Model Results

Couple Households	(1) Fixed effects	(2) Pooled	(3) Fixed effects	(4) Pooled	(5) fixed effects	(6) Pooled
	Durable spending		Risky asset share		Safe asset share	
log(HPU_{12})	-343.509***	-121.639***	-0.019***	-0.058***	0.029***	0.009***
	(59.282)	(37.637)	(0.004)	(0.004)	(0.003)	(0.003)
$\bar{\partial}\log(HPU_{12})$		-51.372		-0.022		0.007
Log-likelihood		-46,940.5		-67,445.2		-89,928.9
Households	2,675	2,675	20,529	20,529	20,529	20,529
Observations	11,510	11,510	116,668	116,668	116,668	116,668
Share censored	0.57	0.57	0.63	0.63	0.36	0.36

Single Households	(7) Fixed effects	(8) Pooled	(9) Fixed effects	(10) Pooled	(11) Fixed effects	(12) Pooled
	Durable spending		Risky asset share		Safe asset share	
log(HPU_{12})	-73.097	6.656	-0.051***	-0.082***	0.052***	0.009
	(55.359)	(34.858)	(0.009)	(0.008)	(0.006)	(0.007)
$\bar{\partial}\log(HPU_{12})$		1.856		-0.020		0.004
Log-likelihood		-29,932.6		-23,810.3		-34,402.8
Households	2,706	2,706	10,469	10,469	10,469	10,469
Observations	10,970	10,970	48,216	48,216	48,216	48,216
Share censored	0.72	0.72	0.76	0.76	0.58	0.58

*, ** and *** denote significance at 10%, 5%, 1% , respectively. Asymptotic standard errors are presented in parentheses. $\bar{\partial}\log(HPU_{12})$ denotes the average marginal effect corresponding to the coefficient of log of the 12-month average of the health care policy uncertainty index. 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.

The results on households' durable consumption for couple households in columns (1) and (2) indicate a negative and significant effect of health care policy uncertainty. The effect is robust to the inclusion of household-fixed effects, and the pooled Tobit model seems to provide a lower bound on its magnitude. The corresponding average marginal effect indicates the decrease in annual durable consumption for a 100% increase in the 12-month average of the health care policy uncertainty. For illustrative purposes, however, it is more interesting to consider the 70% increase, from a value of 110 to 191, that occurred from the 2016 average to the 2017 average. As briefly illustrated in Section 1, the latter year is associated with extensive political efforts to repeal the Affordable Care Act. When faced with such a 70% increase, the results suggest that couple households lower their annual durable spending by about $35. Spread over an entire year, these estimates do not suggest economically relevant differences in durable spending. Further doubt on the effect of health care policy uncertainty on households' consumption is provided in columns (7) and (8), which indicate insignificant effects for single households.

These results contrast Aaberge et al. (2017) and Giavazzi and McMahon (2012), who find a substantive savings-increase for Chinese and German households, respectively, when exposed to higher policy uncertainty caused by political turmoil. Although this potentially reinforces the concern that the early policy uncertainty literature could suffer from confoundedness with other forms of uncertainty, the results should only be compared with caution as the sample, context, and empirical approach vary. Yet, these differences emphasise the limited possibility to extrapolate policy uncertainty results and highlight the need for investigations of US households.

Empirical results in line with theoretical predictions are provided by the estimation results on the risky and safe asset shares. Columns (3) and (9) imply that an increase in health care policy uncertainty is associated with a decrease in investment share in risky assets for both couple and single households. Using the average marginal effect of the pooled Tobit model, the 70% increase in the annual health care policy uncertainty average decreases the risky asset share of couple and single households by approximately 1.4 percentage-points on average. As the pooled Tobit model results are higher in magnitude, however, this is likely an upper bound on the true reduction. Similarly, the results in columns (5)-(6) and (11)-(12) indicate a positive association between health care policy uncertainty and safe asset share. The average marginal effects only point to an increase of approximately 0.5 (0.3) percentage-points for couple (single) households given the 70% health care policy uncertainty increase discussed earlier. The fixed effect results indicate that the true magnitude of the effect is likely somewhat higher.

These estimates are well aligned with previous literature on the effect of health on portfolio choice. Also analysing HRS data, Edwards (2008), Love and Smith (2010), and Rosen and Wu (2004), for example, find that rating health in the worst category of the subjective health measure is associated with a 7%, 1.8%, and 1% decrease in risky asset share, respectively. Given a substantial increase in health care policy uncertainty, a decrease in relative demand for risky assets comparable to the effect of bad health seems plausible. This highlights the importance of health care policy uncertainty as a determinant of households' financial behaviour.

Estimation of the baseline models provides little evidence that health care policy uncertainty causes a relevant decrease in households' consumption. However, the results on the share of risky and safe assets are suggestive of an important link between health care policy uncertainty and households' portfolio choice. As the regressions control for stock market and business cycle uncertainty, estimates point to a health care policy uncertainty channel rather than a broader economic uncertainty effect. To strengthen this claim, I proceed by analysing whether the effects' magnitudes increase with lower health as suggested by Proposition 2.

5.2 Heterogeneous Effects: Concomitant-Variable Latent Class Tobit Model

First insights on the association between households' health and the effect of health care policy uncertainty are gained by applying the concomitant-variable latent class Tobit model. In particular, I test for statistical significance of the concomitant health variables in the prior probability specification to assess whether component-membership corresponding to a higher health care policy uncertainty effect is linked to bad health. The posterior component means provide further evidence on the characteristics of the identified sub-populations.

In this study, only couple households are explicitly investigated for heterogeneous effects. While this restriction is necessary for brevity of results, focusing on couple households seems appropriate as they constitute the majority of the sample. This also alleviates concerns that economic behaviour of singles cannot readily be adjusted due to health impairment. At the same time, the consumption and portfolio choice of couples is likely to have broader macroeconomic implications, as larger household size is associated with higher durable consumption and higher financial wealth. The restriction is also in line with previous research (e.g., Wu, 2003).

Corresponding results are presented in Table 3. Coefficient estimates of the concomitant health variables are in the top panel, where the first component's coefficients are set to 0 for identification. The bottom panel shows the component-specific health care policy uncertainty coefficient. Appendix D.2 provides complete estimation results. The posterior component means of selected variables are shown in Table 4.

Table 3: Latent Class Tobit Model Results – Couple Households

	(1) Durable spending		(2) Risky asset share		(3) Safe asset share	
Prior Probability						
Constant		0.544		2.909***		0.682**
		(0.860)		(0.873)		(0.283)
Subjective health		-0.027		0.189***		0.286***
		(0.095)		(0.070)		(0.045)
Medical history		0.065		0.001		0.005
		(0.123)		(0.08)		(0.051)
Stroke/Heart attack		-0.084		-0.184		0.015
		(0.173)		(0.147)		(0.098)
Physical limitations		-0.025		-0.013		0.084***
		(0.063)		(0.022)		(0.013)
Hospital/Doctor visit		0.493		-0.472		-0.61***
		(0.573)		(0.609)		(0.213)
Health insured		0.017		-0.469**		-0.481***
		(0.238)		(0.203)		(0.125)
Components	*C.1*	*C.2*	*C.1*	*C.2*	*C.1*	*C.2*
$\log(HPU_{12})$	205.068	-384.775**	0.000	-0.059***	0.001	0.028**
	(378.331)	(187.933)	0.015	0.008	(0.001)	(0.01)
$\partial \log(HPU_{12})\big\|_{\bar{X}_C}$	117.69	-151.247	0.000	-0.016	0.001	0.013
Component share	0.278	0.722	0.072	0.928	0.321	0.679
Log-likelihood		-46,832.3		-64,048.2		-61,712.2
Observations	11,510	11,510	116,668	116,668	116,668	116,668

Estimates are calculated using the EM algorithm illustrated in Appendix C. Bootstrapped standard errors are in parentheses. *, ** and *** denote significance at 10%, 5%, 1% , respectively. $\partial \log(HPU_{12})|_{\bar{X}_C}$ denotes the marginal effect at the mean observation of each component as identified using the posterior component means. 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.

As evident by the substantial differences in the health care policy uncertainty coefficient of component 1 and 2 (*C.1* and *C.2*, henceforth), heterogeneous effects are found for all three dependent variables. However, it cannot be readily linked to households' health in the case of durable spending. First, none of the concomitant health variables are significantly associated with the prior component-membership probabilities. Second, the corresponding posterior component means show no substantive differences between households' health variables. To label the components regardless, I calculate the posterior component means of other variables. Yet, no substantive differences in any – including age, education, or wealth – could be identified. While there is heterogeneity in the policy uncertainty effect on durable spending, the estimation results provide little suggestion on its potential causes. Refuting Proposition 2, however, the findings presented here indicate that they are not linked to the observed health variables.

The results on the risky and safe asset share provide contrasting empirical evidence. In particular, the estimates in column (2) and (3) of Table 3 indicate that the subjective health measure is positively associated with *C.2*-membership and insurance coverage is positively as-

Table 4: Posterior Component Means – Couple Households

	subj	*hist*	*shock*	*phys*	*util*	*insur*	Age	No HS	HS	Above coll.	Wealth
Durable spending											
C.1	3.24	1.12	0.25	2.30	0.98	0.75	66.96	0.15	0.32	0.24	4.80
C.2	3.20	1.14	0.24	2.21	0.99	0.76	66.95	0.14	0.31	0.26	5.24
Risky asset share											
C.1	2.97	0.90	0.18	2.28	0.99	0.90	64.37	0.12	0.33	0.26	5.29
C.2	3.16	0.96	0.19	2.39	0.99	0.83	64.45	0.17	0.32	0.23	4.37
Safe asset share											
C.1	2.88	0.84	0.15	1.97	0.99	0.90	63.83	0.09	0.30	0.32	5.45
C.2	3.27	1.00	0.20	2.57	0.98	0.81	64.72	0.20	0.33	0.19	3.99

'No HS', 'HS', and 'Above coll'. denote the education categories 'No high school', 'High school', and 'Above college', respectively. *Italics* denote coded variables defined in Section 3.1. Wealth is in $100,000 2010 Dollars.

sociated with *C.1*-membership. The results on safe asset shares show that in addition to the previous measures, physical limitations are positively associated with *C.2*-membership and a hospital or doctor visit is positively associated with *C.1*-membership. The latter is potentially surprising, however, an increase in health care utilisation *ceteris paribus* is likely strongly associated with better health care coverage (Smith, 1999). Further evidence is provided by the posterior component means. Considering the safe asset results, the mean observation in *C.2* is characterised by subjective health and physical limitations index being 13.5% and 60% worse compared to the mean observation in *C.1*, respectively. The analogues number for risky assets are 6.4% and 4.8%. One potential worry is that the positive association between health and membership in the second component is potentially confounded by wealth – that is, that the estimates instead capture exposure differences through total wealth due to its positive association with health (Smith, 1999). Two arguments speak against this concern. First, Fan and Zhao (2009) suggest that health does not affect portfolio choice through changes in financial wealth, as they find no effect of health on financial wealth of older Americans. Second, in addition to the four health measures, the prior probability specification includes two health care variables that are positively associated with wealth. Results indicate a household with worse subjective health and more physical limitation is significantly more likely to belong to component two, keeping insurance and health care utilisation fixed. *Ceteris paribus*-analysis thus indicates that component-membership is associated with health exceeding the potential confoundedness through total wealth as captured by better insurance coverage. Therefore, it seems justified to link the components of columns (2) and (3) to households' health. Following Deb and Trivedi's (1997; 2002) terminology, *C.1* and *C.2* are labelled as 'healthy' and 'ill', respectively.

As indicated by the bottom panel of Table 3, observations of the ill component are negatively affected by an increase in uncertainty. Facing a 70% increase in the annual health care policy uncertainty average such as the one from 2016-2017, the mean household in the ill component decreases its investment share in risky assets by about 1.1 percentage-points, and increases its share in safe assets by about 1 percentage-point[35]. In contrast, the mean household in the

[35] Contrasting the pooled Tobit model, average marginal effects cannot be calculated as observations are not explicitly assigned to a component. As an alternative, marginal effects for each component's average observation

healthy component is not significantly affected by health care policy uncertainty. The magnitude of these estimates is in line with the literature on the effect of health on portfolio choice as illustrated in the previous section. Their importance is further highlighted by the average prior probability of each component, which are usually interpreted as each component's population share (Kamakura & Russell, 1989). Values are presented in Table 3. As approximately 68% to 93% of the sample seems to be strongly negatively affected, health care policy uncertainty is an important determinant of financial behaviour for the majority of older American couples. The results are thus not driven by few unusual observations, but instead reflect a prevalent data pattern. These findings provide strong empirical support for the claim of Proposition 2 that less healthy households reduce their relative demand for risky assets more strongly when exposed to health care policy uncertainty.

5.3 Heterogeneous Effects: Tobit Model-Based Recursive Partitioning

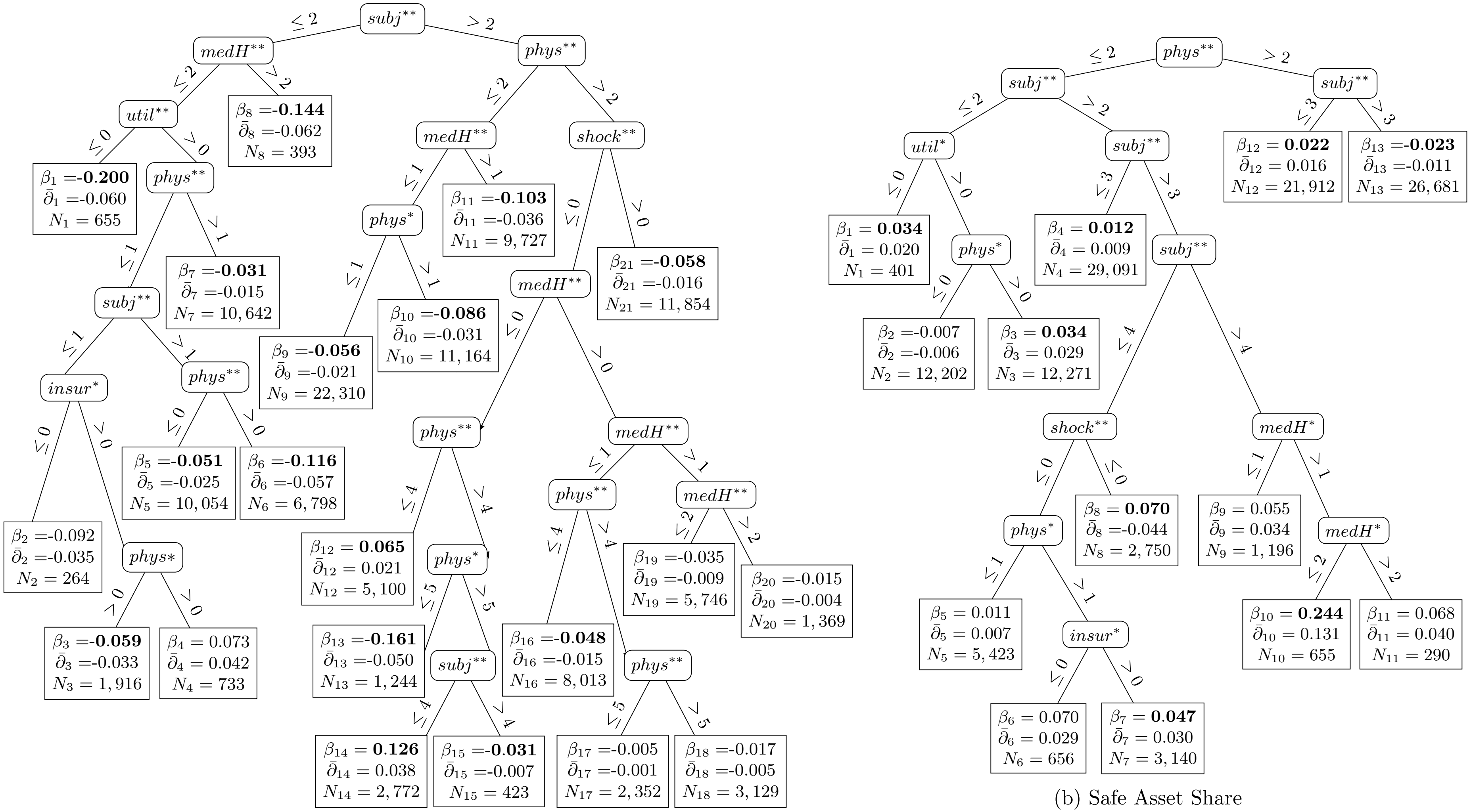
Results in the previous section provide support for the claim of Proposition 2 on the relative demand of risky assets. However, insights from the latent class model are limited. In addition to allowing for a higher number of subpopulations, Tobit model-based recursive partitioning also allows the effect of the health variables to be non-linear and highly interactive, making it most suitable for in-depth analysis of heterogeneity in the effect of health care policy uncertainty.

The model-based recursive partitioning results for the risky and safe asset shares are presented in Figure 2. Connecting nodes (rounded corners) state the feature with the most significant rejection of parameter-stability, and terminal nodes (sharp corners) present the coefficient of the log-transformed annual health care policy uncertainty average, its average marginal effect, and the sub-sample size. Subscripts indicate the node numbering. Complete estimation results are in Appendix D.3. The model-based recursive partitioning results did not indicate any parameter instability in the health care policy uncertainty coefficient along the health variables when analysing durable consumption for couple and single households. This highlights the procedure's shortcoming compared to a latent class model; its requirement for a strong association between partition-membership and partitioning features (Frick et al., 2014). For the question at hand, the finding is nevertheless insightful as it corroborates the results of the previous section by providing further evidence against the claim that health is linked to the decrease of households' durable consumption when exposed to health care policy uncertainty.

Due to the wealth of partitioning results, a structured approach is necessary to make inferences on heterogeneity in the health care policy uncertainty effect. Before turning to the direction of the heterogeneity, I thus begin by describing *how* parameter differences are captured. As indicated by the numerous sample splits for both risky and safe asset shares, the Tobit model-based recursive partitioning procedure provides evidence that substantial heterogeneity in the effect of health care policy uncertainty is captured by the observed health variables[36]. In particular, the subjective health, physical limitation and medical history measures seem to be strongly associated with coefficient instability given their frequency in the tree. In contrast, the health care variables on utilisation and insurance seem to capture less of the coefficient heterogeneity.

(defined by the posterior component means) are used for interpretation.

[36]The frequent splits are evidence of a highly non-linear and interactive effect of health and thus provide strong support for the methodological decision not to employ a multiplicative-interaction model in this study.



(a) Risky Asset Share

(b) Safe Asset Share

Figure 2: Tobit Model-Based Recursive Partitioning Tree – Couple Households

The feature with the most significant rejection of parameter-stability is stated in each connecting node (rounded corners), with ** and * indicating significance at 1% and 5%, respectively. *Italics* denote coded variables defined in Section 3.1. Terminal nodes (sharp corners), state the coefficient the log-transformed annual health care policy uncertainty average (β), the corresponding average marginal effect ($\bar{\partial}$), and the partition's sample size (N). 5% significance of coefficients is indicated by bold print. Subscripts indicate the node numbering. 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. Complete estimation results are in Appendix D.3.

The lesser importance of the latter is in line with previous research. For example, Rosen and Wu (2004) find no substantial effects of health insurance on portfolio choice.

To assess the association between health and parameter heterogeneity, it is important to establish which partitions are deemed less healthy. This is, unfortunately, not always possible. The problem arises as it is unclear how health can be ranked across health measures. For example, while partition (9) of Figure 2a can be characterised as more healthy than partition (10) given the latter's strictly higher physical limitations, the comparison of partition (10) and (11) is ambiguous. The reason for this is that existing research provides no empirical evidence as to whether, in this case, two or more historical conditions (e.g., diabetes) or a higher number of physical limitations (e.g. not being able to walk a block) is more determinate of bad health[37]. While it is possible to hypothesise, I aim to avoid this ambiguity in comparing the observed health measures and focus on sub-trees that allow for straightforward interpretation.

With this strategy, the results can be analysed to support or refute Proposition 1 and 2. First, Tobit model-based recursive partitioning identifies a few subsamples with estimation results contrasting those of the previous models. In particular, nodes (12) and (14) in Figure 2a and node (13) in Figure 2b. Nevertheless, the large majority of partitions shows a negative (positive) significant effect of health care policy uncertainty on the risky (safe) asset share. The claim that health care policy uncertainty decreases relative demand for risky assets thus seems robust to model specification. Second, many sub-trees show a more substantial effect of health care policy uncertainty with worsening health. Examples include the pairs (5,6) and (9,10) in Figure 2a and pairs (2,3) and (9,10) in Figure 2b. Considering the results in the first pair (5,6), a household with 'very good' subjective health ($subj$=2), less or equal than two historical medical conditions, with at least one doctor or hospital visit in the previous two years, and *no* physical limitations reduces risky asset investment share by 2.2 percentage-points more than a comparable household with *at least one* physical limitation when faced with a 70% increase in the annual health care policy uncertainty average. While this provides some evidence that health magnifies the effect of health care policy uncertainty, the claim that health has a strictly one-directional effect cannot be supported in general. For example, consider the sub-tree (9,10,11) in Figure 2b. The three nodes are increasing in the households' medical history, yet, while the effect of health care policy uncertainty is lowest in node (9) as expected, the effect of health care policy uncertainty is highest in node (10) rather than node (11)[38]. A possible explanation for these results is the potential decrease of consumption utility and expected life-span with worse health (Smith, 1999). As illustrated in Section 2.1, if this effect of health overweights its impact on medical expenditures, then the health care policy uncertainty effect is *decreasing* in health issues. The presented results seem to suggest that this occurs for households with particularly bad health.

While the Tobit model-based recursive partitioning results corroborate the negative effect of health care policy uncertainty on households' relative demand for risky asset, there is some evidence against a strictly one-directional effect of health on the impact of health care uncertainty. Nevertheless, the results show that the magnitude of the coefficient of health care policy uncertainty is strongly associated with observed health variables and that the a higher effect of

[37]Love and Smith (2010) employ similar health indices, but provide no evidence on their levels of severity.
[38]Similar examples are given by the sub-trees (12,13,14,15) and (16,17,18,19,29) in Figure 2a.

health care policy uncertainty seems to be at least partly associated with worse health.

6 Conclusion

This study analyses the effect of health care policy uncertainty on households' consumption and portfolio choice. A simple model is developed to motivate a negative effect on consumption and relative demand for risky financial assets, and to illustrate a potentially magnifying impact of bad health on the effect of health care policy uncertainty. Using the HRS' rich longitudinal data on older Americans and Baker et al.'s (2016) recently developed health care policy uncertainty index, these theoretical claims are tested using a censored fixed effect model, a concomitant-variable latent class Tobit model, and a Tobit model-based recursive partitioning procedure. No sufficient empirical evidence is found to support that health care policy uncertainty negatively affects households' durable consumption. In contrast, the estimates indicate a substantive negative effect of health care policy uncertainty on households' relative demand for risky assets. Further evidence corroborates the magnifying impact of bad health on the effect on portfolio choice. As these results do not appear to be driven by potentially endogenous household characteristics or other confounding forms of uncertainty, this study indicates that health care policy uncertainty is an important determinant of households' financial behaviour.

The empirical evidence not only suggests that higher health care policy uncertainty is associated with a welfare loss of individual households, but also points to substantive macroeconomic consequences. The estimates suggest that an uncertainty increase similar to the repeal efforts of the Affordable Care Act in 2017 decreases the relative demand for stocks and mutual funds as much as a considerable reduction in health (e.g., Rosen & Wu, 2004). This is effect is not driven by few households, but is a prevalent pattern that is found for about 68% to 93% of older American couples. Given their large share of financial assets, the reduction in stock market participation has direct consequences on stock market volatility (Allen & Gale, 1994), the equity premium (Mankiw & Zeldes, 1991), and wealth inequality (Favilukis, 2013). The latter is particularly grave as health care policy uncertainty disproportionally affects less healthy households, which exacerbates the socio-economic disadvantage associated with bad health in the US (Smith, 1999). As health care policy uncertainty and its implications are likely to persist in the foreseeable future[39], these costs seem relevant for both legislatures and voters.

This study makes first contributions to the analysis of health care policy uncertainty, but many policy questions remain. For example, it is unclear how transparent communication of health care reform plans would affect uncertainty. Although it could have a decreasing effect through reducing misinformation, such news can foreground the possibility of policy changes, potentially increasing uncertainty. Further, while limiting legislative bodies' abilities to delay reforms or revoke policies adopted by previous governments might lower uncertainty, it could also impede interventions necessary to address uncertainty. A promising alternative is to reduce the political component of health care policy uncertainty. In particular as health care continues to be a major topic in national election campaigns, assessing how constructive debate can be distinguished from political exploit is important. I leave these avenues to future research.

[39] Just in the process of writing, health care policy uncertainty experienced yet another spike with the US Justice Department joining a lawsuit against some of the Affordable Care Acts provisions, including the rule prohibiting the denial of health care to people with pre-existing medical conditions (Barnes, 2018).

References

Aaberge, R., Liu, K., & Zhu, Y. (2017). Political uncertainty and household savings. *Journal of Comparative Economics*, *45*(1), 154–170.

Addoum, J. M. (2017). Household portfolio choice and retirement. *Review of Economics and Statistics*, *99*(5), 870–883.

Agarwal, V., Aslan, H., & Ren, H. (2018). *Policy uncertainty and household stock market participation.* (CFR working paper.)

Aitkin, M., & Rubin, D. B. (1985). Estimation and hypothesis testing in finite mixture models. *Journal of the Royal Statistical Society. Series B (Methodological)*, *47*(1), 67–75.

Allen, F., & Gale, D. (1994). Limited market participation and volatility of asset prices. *American Economic Review*, *84*(4), 933–955.

Atella, V., Brunetti, M., & Maestas, N. (2012). Household portfolio choices, health status and health care systems: A cross-country analysis based on share. *Journal of Banking & Finance*, *36*(5), 1320–1335.

Athey, S. (2017). Beyond prediction: Using big data for policy problems. *Science*, *355*(6324), 483–485.

Athey, S. (2018). The impact of machine learning on economics: An agenda. In A. K. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (chap. 21). Chicago: University of Chicago Press.

Athey, S., & Imbens, G. W. (2015). *Machine learning methods for estimating heterogeneous causal effects.* (Stanford University working paper.)

Athey, S., & Imbens, G. W. (2017). The state of applied econometrics: Causality and policy evaluation. *Journal of Economic Perspectives*, *31*(2), 3–32.

Attanasio, O. P. (1999). Consumption. In J. B. Taylor & M. Woodford (Eds.), *Handbook of macroeconomics* (Vol. 1, pp. 741–812). Amsterdam: Elsevier.

Bago d'Uva, T. (2006). Latent class models for utilisation of health care. *Health Economics*, *15*(4), 329–343.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Baker, S. R., Bloom, N., & Davis, S. J. (2018). *Health care policy uncertainty index.* (Retrieved on May 15, 2018, from `http://www.policyuncertainty.com/categorical_epu.html`.)

Barnes, R. (2018, Jun). Trump administration shifted positions in a lawsuit against Affordable Care Act. It wasn't first legal about-face. *The Washington Post*. (Retrieved on June 15, 2018, from `https://www.washingtonpost.com/politics/courts_law/trump-administration-shifted-positions-in-a-lawsuit-against-affordable-care-act-it-wasnt-first-legal-about-face/2018/06/08/c0dd30a8-6b33-11e8-9e38-24e693b38637_story.html?utm_term=.7b5a608a4ec8`.)

Berkowitz, M. K., & Qiu, J. (2006). A further look at household portfolio choice and health status. *Journal of Banking & Finance*, *30*(4), 1201–1217.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–76.

Bodie, Z., Merton, R. C., & Samuelson, W. F. (1992). Labor supply flexibility and portfolio choice in a life cycle model. *Journal of Economic Dynamics and Control*, *16*(3-4), 427–449.

Bureau of Economic Analysis. (2018). *Table 2.5.5. Personal Consumption Expenditures by Function.* (Retrieved on May 20, 2018, from `https://www.bea.gov/iTable/iTableHtml.cfm?reqid=19&step=3&isuri=1&1921=survey&1903=74`.)

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications.* Cambridge: Cambridge University Press.

Cardak, B. A., & Wilkins, R. (2009). The determinants of household risky asset holdings: Australian evidence on background risk and other factors. *Journal of Banking & Finance*, *33*(5), 850–860.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly Journal of Economics*, *112*(1), 1–55.

Carroll, C. D., & Samwick, A. A. (1998). How important is precautionary saving? *Review of Economics and Statistics*, *80*(3), 410–419.

Chacko, G., & Viceira, L. M. (2005). Dynamic consumption and portfolio choice with stochastic volatility in incomplete markets. *The Review of Financial Studies*, *18*(4), 1369–1402.

Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1), 18–38.

Coile, C., & Milligan, K. (2009). How household portfolios evolve after retirement: The effect of aging and health shocks. *Review of Income and Wealth*, *55*(2), 226–248.

Crossley, T. F., Low, H., & O'Dea, C. (2013). Household consumption through recent recessions. *Fiscal Studies*, *34*(2), 203–229.

Currie, J., & Madrian, B. C. (1999). Health, health insurance and the labor market. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 3, pp. 3309–3416). Amsterdam: Elsevier.

Dayton, C. M., & Macready, G. B. (1988). Concomitant-variable latent-class models. *Journal of the American Statistical Association*, *83*(401), 173–178.

Deb, P., & Trivedi, P. K. (1997). Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics*, *12*(3), 313–336.

Deb, P., & Trivedi, P. K. (2002). The structure of demand for health care: Latent class versus two-part models. *Journal of Health Economics*, *21*(4), 601–625.

Delavande, A., & Rohwedder, S. (2011). Individuals' uncertainty about future social security benefits and portfolio choice. *Journal of Applied Econometrics*, *26*(3), 498–519.

Edwards, R. D. (2008). Health risk and portfolio choice. *Journal of Business & Economic Statistics*, *26*(4), 472–485.

Elmendorf, D. W., & Kimball, M. S. (2000). Taxation of labor income and the demand for risky assets. *International Economic Review*, *41*(3), 801–832.

Fan, E., & Zhao, R. (2009). Health status and portfolio choice: Causality or heterogeneity? *Journal of Banking & Finance*, *33*(6), 1079–1088.

Favilukis, J. (2013). Inequality, stock market participation, and the equity premium. *Journal of Financial Economics*, *107*(3), 740–759.

Ferraro, K. F. (1980). Self-ratings of health among the old and the old-old. *Journal of Health and Social Behavior*, *21*(4), 377–383.

Frick, H., Strobl, C., & Zeileis, A. (2014). To split or to mix? Tree vs. mixture models for detecting subgroups. *COMPSTAT 2014–Proceedings in Computational Statistics*, 379–386.

Fuchs-Schündeln, N., & Schündeln, M. (2005). Precautionary savings and self-selection: Evidence from the German reunification "experiment". *The Quarterly Journal of Economics*, *120*(3), 1085–1120.

Gábor-Tóth, E., & Georgarakos, D. (2018). *Economic policy uncertainty and stock market participation.* (CFS working paper.)

Giavazzi, F., & McMahon, M. (2012). Policy uncertainty and household savings. *Review of Economics and Statistics*, *94*(2), 517–531.

Goldman, D., & Maestas, N. (2013). Medical expenditure risk and household portfolio choice. *Journal of Applied Econometrics*, *28*(4), 527–550.

Gollier, C., & Pratt, J. W. (1996). Risk vulnerability and the tempering effect of background risk. *Econometrica*, *64*(5), 1109–1123.

Greene, W. (2004). Fixed effects and bias due to the incidental parameters problem in the Tobit model. *Econometric Reviews*, *23*(2), 125–147.

Gruber, J., & Yelowitz, A. (1999). Public health insurance and private savings. *Journal of Political Economy*, *107*(6), 1249–1274.

Guiso, L., Jappelli, T., & Terlizzese, D. (1992). Earnings uncertainty and precautionary saving. *Journal of Monetary Economics*, *30*(2), 307–337.

Guiso, L., Jappelli, T., & Terlizzese, D. (1996). Income risk, borrowing constraints, and portfolio choice. *American Economic Review*, *86*(1), 158–172.

Hainmueller, J., Mummolo, J., & Xu, Y. (2018). How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice. *Political Analysis*. (Forthcoming.)

Health and Retirement Study. (2018a). *Harmonized HRS (v.A).* (Produced by the USC Program on Global Aging, Health, and Policy, with funding and support from the National Institute on Aging (NIA.).)

Health and Retirement Study. (2018b). *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. (2018c). *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.)

Heij, C., De Boer, P., Franses, P. H., Kloek, T., & Van Dijk, H. K. (2004). *Econometric methods with applications in business and economics.* Oxford: Oxford University Press.

Hochguertel, S. (2003). Precautionary motives and portfolio decisions. *Journal of Applied Econometrics*, *18*(1), 61–77.

Honoré, B. E. (1992). Trimmed lad and least squares estimation of truncated and censored regression models with fixed effects. *Econometrica*, *60*(3), 533–565.

Honoré, B. E. (2002). Nonlinear models with panel data. *Portuguese Economic Journal*, *1*(2), 163–179.

Hothorn, T., & Zeileis, A. (2015). partykit: A modular toolkit for recursive partytioning in R. *The Journal of Machine Learning Research*, *16*(1), 3905–3909.

Johnson, J. (2017, Jul). Trump's grand promises to 'very, very quickly' repeal Obamacare run into reality. *The Washington Post*. (Retrieved on June 15, 2018, from https://www.washingtonpost.com/politics/trumps-grand-promises-to-very-very-quickly-repeal-obamacare-run-into-reality/2017/07/18/91b5f220-6bd3-11e7-9c15-177740635e83_story.html?noredirect=on&utm_term=.04a354c7ca5d.)

Kamakura, W. A., & Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research*, *26*(4), 379–390.

Kamakura, W. A., Wedel, M., & Agrawal, J. (1994). Concomitant variable latent class models for conjoint analysis. *International Journal of Research in Marketing*, *11*(5), 451–464.

Karlsson, M., & Laitila, T. (2014). Finite mixture modeling of censored regression models. *Statistical Papers*, *55*(3), 627–642.

Kimball, M. S. (1990a). *Precautionary saving and the marginal propensity to consume.* (NBER working paper.)

Kimball, M. S. (1990b). Precautionary saving in the small and in the large. *Econometrica*, *58*(1), 53–73.

Kimball, M. S. (1993). Standard risk aversion. *Econometrica*, *61*(3), 589–611.

Laird, N. (1978). Nonparametric maximum likelihood estimation of a mixing distribution. *Journal of the American Statistical Association*, *73*(364), 805–811.

LaRue, A., Bank, L., Jarvik, U., & Hetland, M. (1979). Health in old age: How do physicians' ratings and self-ratings compare? *Journal of Gerontology*, *34*(5), 687–691.

Levin, L. (1995). Demand for health insurance and precautionary motives for savings among the elderly. *Journal of Public Economics*, *57*(3), 337–367.

Lindeboom, M., & Kerkhofs, M. (2009). Health and work of the elderly: Subjective health measures, reporting errors and endogeneity in the relationship between health and work. *Journal of Applied Econometrics*, *24*(6), 1024–1046.

Love, D. A., & Smith, P. A. (2010). Does health affect portfolio choice? *Health Economics*, *19*(12), 1441–1460.

Lusardi, A. (1998). On the importance of the precautionary saving motive. *American Economic Review*, *88*(2), 449–453.

Luttmer, E. F., & Samwick, A. A. (2018). The welfare cost of perceived policy uncertainty: Evidence from social security. *American Economic Review*, *108*(2), 275–307.

Mankiw, N. G., & Zeldes, S. P. (1991). The consumption of stockholders and non-stockholders. *Journal of Financial Economics*, *29*(1), 97–111.

Mazzocco, M. (2004). Saving, risk sharing, and preferences for risk. *American Economic Review*, *94*(4), 1169–1182.

McLachlan, G., & Peel, D. (2004). *Finite mixture models.* New York: John Wiley & Sons.

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87–106.

Obama, B. (2016). United States health care reform: Progress to date and next steps. *Journal of the American Medical Association*, *316*(5), 525-532.

Poterba, J. M. (1994). Govemment saving incentives in the United States. In J. M. Poterba (Ed.), *Public policies and household savings* (Vol. 1, pp. 1–18). Chicago: University of Chicago Press.

Pratt, J. W., & Zeckhauser, R. J. (1987). Proper risk aversion. *Econometrica*, *55*(1), 143–154.

Rosen, H. S., & Wu, S. (2004). Portfolio choice and health status. *Journal of Financial Economics*, *72*(3), 457–484.

Rusch, T., & Zeileis, A. (2013). Gaining insight with recursive partitioning of generalized linear models. *Journal of Statistical Computation and Simulation*, *83*(7), 1301–1315.

Skinner, J. (1988). Risky income, life cycle consumption, and precautionary savings. *Journal of Monetary Economics*, *22*(2), 237–255.

Smith, J. P. (1999). Healthy bodies and thick wallets: The dual relation between health and economic status. *Journal of Economic Perspectives*, *13*(2), 145–166.

Starr-McCluer, M. (1996). Health insurance and precautionary savings. *American Economic Review*, *86*(1), 285–295.

Stephens, M., Jr. (2002). Worker displacement and the added worker effect. *Journal of Labor Economics*, *20*(3), 504–537.

Stock, J. H., & Watson, M. W. (2012). Disentangling the channels of the 2007—09 recession. *Brookings Papers on Economic Activity*, *Spring*, 81–156.

Strobl, C., Kopf, J., & Zeileis, A. (2015). Rasch trees: A new method for detecting differential item functioning in the Rasch model. *Psychometrika*, *80*(2), 289–316.

Strobl, C., Wickelmaier, F., & Zeileis, A. (2011). Accounting for individual differences in Bradley-Terry models by means of recursive partitioning. *Journal of Educational and Behavioral Statistics*, *36*(2), 135–153.

Suderman, P. (2017, Nov). Why we're still fighting over the health care mandate (op-ed). *The New York Times*. (Retrieved on June 15, 2018, from `https://www.nytimes.com/2017/11/15/opinion/republican-tax-plan-health-care.html`.)

The Conference Board. (2001). *Business cycle indicators handbook.*

The Conference Board. (2018). *Coincident Economic Index® (CEI).*

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`.)

United States Congress. (2010). *The Patient Protection and Affordable Care Act, 42 U.S.C. § 18001 et seq.* (Accessed on July 3, 2018, at `https://www.gpo.gov/fdsys/pkg/PLAW-111publ148/pdf/PLAW-111publ148.pdf`.)

Van der Heijden, P. G., Dessens, J., & Bockenholt, U. (1996). Estimating the concomitant-variable latent-class model with the EM algorithm. *Journal of Educational and Behavioral Statistics*, *21*(3), 215–229.

Wager, S., & Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*. (Forthcoming.)

Wagner, M., & Zeileis, A. (2018). Heterogeneity and spatial dependence of regional growth in the EU: A recursive partitioning approach. *German Economic Review*. (Forthcoming.)

Wedel, M., DeSarbo, W. S., Bult, J. R., & Ramaswamy, V. (1993). A latent class Poisson regression model for heterogeneous count data. *Journal of Applied Econometrics*, *8*(4), 397–411.

Wu, C. J. (1983). On the convergence properties of the EM algorithm. *The Annals of Statistics*, *11*(1), 95–103.

Wu, S. (2003). The effects of health events on the economic status of married couples. *Journal of Human Resources*, *38*(1), 219–230.

Yahoo Finance. (2018a). *Implied Volatility Index (VIX).* (Retrieved on June 20, 2018, from `https://finance.yahoo.com/quote/%5EVIX?p=^VIX`.)

Yahoo Finance. (2018b). *S&P 500 Real Time Price.* (Retrieved on June 20, 2018, from `https://finance.yahoo.com/quote/%5EGSPC?p=^GSPC`.)

Zeileis, A., & Hornik, K. (2007). Generalized m-fluctuation tests for parameter instability. *Statistica Neerlandica*, *61*(4), 488–508.

Zeileis, A., Hothorn, T., & Hornik, K. (2008). Model-based recursive partitioning. *Journal of Computational and Graphical Statistics*, *17*(2), 492–514.

Zeldes, S. P. (1989). Optimal consumption with stochastic income: Deviations from certainty equivalence. *The Quarterly Journal of Economics*, *104*(2), 275–298.

Appendices

A Proof of Proposition 1 and 2

This section provides a proof for Proposition 1 and 2 of the model developed in Section 2.1.

Preliminaries. For ease of notation, define $[C_1^*, x^*]$ to be the maximising arguments in the case of no uncertainty about P, and define $[\tilde{C}_1^*, \tilde{x}^*]$ to be the maximising arguments in the case of uncertainty about P. Then, Proposition 1 can be expressed by

$$C_1^* > \tilde{C}_1^* \qquad \text{and} \qquad x^* > \tilde{x}^* \tag{16}$$

and Proposition 2 can be expressed by

$$C_1^*(h_g) - \tilde{C}_1^*(h_g) < C_1^*(h_b) - \tilde{C}_1^*(h_b) \qquad \text{and} \qquad x^*(h_g) - \tilde{x}^*(h_g) < x^*(h_b) - \tilde{x}^*(h_b) \tag{17}$$

where consumption and investment are expressed as a function of required units of treatment (i.e., health) with $h_g < h_b$.

Because the expectation is a positive linear operation, $U(C)$ is strictly concave in C, and C_2 is linear in C_1 and x, proving (16) and (17) is equivalent to proving

$$\begin{aligned} & \frac{\partial E[U(C_1) + U(C_2)]}{\partial C_1} > \frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial C_1} \\ \text{and} \quad & \frac{\partial E[U(C_1) + U(C_2)]}{\partial x} > \frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial x} \end{aligned} \tag{18}$$

where $\tilde{E}$ denotes the expectation under uncertainty about P, as well as

$$\begin{aligned} & \left.\frac{\partial E[U(C_1) + U(C_2)]}{\partial C_1}\right|_{h_g} - \left.\frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial C_1}\right|_{h_g} < \left.\frac{\partial E[U(C_1) + U(C_2)]}{\partial C_1}\right|_{h_b} - \left.\frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial C_1}\right|_{h_b} \\ \text{and} \quad & \left.\frac{\partial E[U(C_1) + U(C_2)]}{\partial x}\right|_{h_g} - \left.\frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial x}\right|_{h_g} < \left.\frac{\partial E[U(C_1) + U(C_2)]}{\partial x}\right|_{h_b} - \left.\frac{\partial \tilde{E}[U(C_1) + U(C_2)]}{\partial x}\right|_{h_b} \end{aligned} \tag{19}$$

where the left-hand side corresponds to an individual with lower required units of treatment ($h_g < h_b$).

For the case of no uncertainty about P, the first order conditions with respect to C_1 and x

are given by

$$0 = \frac{\partial E[U(C_1)+U(C_2)]}{\partial C_1} = \frac{\partial U(C_1)}{\partial C_1} - p_1\big(1+xr_1+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^1} - p_2\big(1+xr_2+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^2} \tag{20}$$

$$0 = \frac{\partial E[U(C_1)+U(C_2)]}{\partial x} = p_1\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^1} + p_2\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^2} \tag{21}$$

For the case of uncertainty about P, the first order conditions with respect to C_1 and x are given by

$$\begin{aligned}0 = \frac{\partial E[U(C_1)+U(C_2)]}{\partial C_1} = \frac{\partial U(C_1)}{\partial C_1} &- p_{11}\big(1+xr_1+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{11}} \\ &- p_{12}\big(1+xr_1+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{12}} \\ &- p_{21}\big(1+xr_2+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{21}} \\ &- p_{22}\big(1+xr_2+(1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{22}}\end{aligned} \tag{22}$$

$$\begin{aligned}0 = \frac{\partial E[U(C_1)+U(C_2)]}{\partial x} = \; & p_{11}\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{11}} \\ &+ p_{12}\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{12}} \\ &+ p_{21}\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{21}} \\ &+ p_{22}\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{22}}\end{aligned} \tag{23}$$

Lemmas. It is useful to begin by deriving two inequalities.

First, for a given positive share invested in the risky asset ($x > 0$) and a given level of consumption in period 1 (C_1), it holds that

$$p_{i1}\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i1}} + p_{i2}\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i2}} > p_i\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i}} \tag{24}$$

$$\leftrightarrow \quad p_i\left(p_1^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i1}} + p_2^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i2}}\right) > p_i\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i}} \tag{25}$$

$$\leftrightarrow \quad p_1^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i1}} + p_2^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i2}} > \frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{i}} \tag{26}$$

where the left-hand side corresponds to the case of uncertainty about cost of per-unit treatment and the right-hand side to the certainty case. Equation (26) holds due to the decreasing absolute risk aversion: it follows that the increase in slope between $\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^i} < \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{i1}}$ relative to the decrease in slope between $\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{i2}} > \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^i}$ is larger than the decrease in value between $C_2^i > C_2^{i1}$ relative to the increase in value between $C_2^i < C_2^{i2}$. As C_2^i is given by the linear relation $p_1^H C_2^{i1} + p_2^H C_2^{i2}$, equation (26) follows.

Third, consider the relative increase in expected marginal effect of equation (26) at the two realisations of risky asset returns r_1 and r_2, where $r_1 < r_2$. Because of decreasing absolute prudence, it holds that

$$\frac{p_1^H \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{11}} + p_2^H \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{12}}}{\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^1}} > \frac{p_1^H \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{21}} + p_2^H \frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{22}}}{\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^2}} \tag{27}$$

where the right-hand side corresponds to the case with low return of the risky asset r_1, the left-hand side corresponds to the case with high return of the risky asset r_2, and the nominators and denominators correspond to the case of uncertainty and no-uncertainty about the per-unit cost of treatment, respectively. Intuitively, this states that the relative effect of the introduction of uncertainty about the per-unit cost of treatment is more substantial at lower levels of consumption (i.e., with low returns of the risky asset r_1) compared to the relative effect at higher levels of consumption (i.e., with high returns of the risky asset r_2).

Proposition 1.1. We first derive that the individual decreases consumption in period 1 (C_1) after the introduction of uncertainty about the per-unit cost of treatment. For this purpose, consider the first order conditions (20) and (22). From the inequality (24), it follows that

$$\begin{aligned} &p_1\big(1 + xr_1 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^1} + p_2\big(1 + xr_2 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^2} \\ &< p_{11}\big(1 + xr_1 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{11}} + p_{12}\big(1 + xr_1 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{12}} \\ &\quad + p_{21}\big(1 + xr_2 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{21}} + p_{22}\big(1 + xr_2 + (1-x)b\big)\frac{\partial U(C_2)}{\partial C_2}\Big|_{C_2=C_2^{22}} \end{aligned} \tag{28}$$

For the first order conditions to hold, $\frac{\partial U(C_1)}{\partial C_1}$ corresponding to the case of uncertainty must be larger than in the case of certainty. As $U(C)$ is increasing and concave, this implies that C_1 corresponding to the case of uncertainty must be smaller than in the case of certainty.

Proposition 1.2. Next, we show that the individual decreases her investment share in the risky asset (x) after the introduction of uncertainty about the per-unit cost of treatment. Consider the optimal choice of investment share in the risky asset *without* any uncertainty about the per-unit cost of treatment: x^*. For optimality, the corresponding first order condition (21) at

x^* is required to be zero – that is,

$$
\begin{aligned}
0 = \frac{\partial E[U(C_1)+U(C_2)]}{\partial x}\bigg|_{x=x^*}^{certainty} &= p_1\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}} \\
&\quad + p_2\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{2*}} \\
&= (W_0-C_1)\bigg(p_1(r_1-b)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}} \\
&\quad + p_2(r_2-b)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{2*}}
\end{aligned}
\tag{29}
$$

This can be compared to the first order condition at the same x^* in case of uncertainty about the per-unit cost of treatment (23):

$$
\begin{aligned}
\frac{\partial E[U(C_1)+U(C_2)]}{\partial x}\bigg|_{x=x^*}^{uncertainty} &= p_{11}\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{11*}} \\
&\quad + p_{12}\big((W_0-C_1)(r_1-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{12*}} \\
&\quad + p_{21}\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{21*}} \\
&\quad + p_{22}\big((W_0-C_1)(r_2-b)\big)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{22*}} \\
&= (W_0-C_1)\bigg(p_1(r_1-b)\bigg(p_1^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{11*}} + p_2^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{12*}}\bigg) \\
&\quad + p_2(r_2-b)\bigg(p_1^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{21*}} + p_2^H\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{22*}}\bigg)\bigg)
\end{aligned}
\tag{30}
$$

From inequality (24), it follows that we can write the change from the first order condition under certainty about per-unit treatment cost given by equation (29) upon the introduction of uncertainty to equation (30) by

$$
\begin{aligned}
\frac{\partial E[U(C_1)+U(C_2)]}{\partial x}\bigg|_{x=x^*}^{uncertainty} &= (W_0-C_1)\bigg(p_1(r_1-b)\bigg(y\times\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}}\bigg) \\
&\quad + p_2(r_2-b)\bigg(z\times\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{2*}}\bigg)\bigg)
\end{aligned}
\tag{31}
$$

where y and z is the relative increase in expected slope in case of low and high returns on the risky asset, respectively. By (27), we know that $y > z$. Hence, we can write $y = (z+\delta)$. This results in

$$
\begin{aligned}
\frac{\partial E[U(C_1)+U(C_2)]}{\partial x}\bigg|_{x=x^*}^{uncertainty} &= (W_0-C_1)\Big(p_1(r_1-b)\Big(y\times \frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}}\Big) \\
&\quad + p_2(r_2-b)\Big(z\times \frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{2*}}\Big)\Big) \\
&= z\times \Big((W_0-C_1)\Big(p_1(r_1-b)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}} \\
&\quad + p_2(r_2-b)\frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{2*}}\Big)\Big) \\
&\quad + p_1(W_0-C_1)(r_1-b)\Big(\delta\times \frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}}\Big) \\
&= p_1(W_0-C_1)(r_1-b)\Big(\delta\times \frac{\partial U(C_2)}{\partial C_2}\bigg|_{C_2=C_2^{1*}}\Big) \\
&< \frac{\partial E[U(C_1)+U(C_2)]}{\partial x}\bigg|_{x=x^*}^{certainty} = 0
\end{aligned} \tag{32}
$$

where the last inequality is given by $(r_1-b)<0$ and the remaining terms being positive. As the marginal effect of an additional unit of x is negative at the value $x*$ in the case of uncertainty about the per-unit cost of treatment, we can conclude that the optimal investment share in the risky asset is lower compared to the case of no uncertainty about the per-unit cost of treatment.

Proposition 2. Finally, we show that the effects stated in Proposition 1 are higher for individuals with bad health status compared to individuals with good health status.

Denote the two individuals' required units of health care treatment by h_b and h_g where $h_b>h_g$ (the higher, the worse). As consumption in period 2 is given by $C_2^{ijb}=(W_0-C_1)(1+xr_i+(1-x)b)-h_b*P_j$ and $C_2^{ijg}=(W_0-C_1)(1+xr_i+(1-x)b)-h_g*P_j$ for $(i,j)\in\{1,2\}\times\{1,2\}$ for bad and good health status, respectively, it holds that $Var(C_2^{ijb})>Var(C_2^{ijg})$. Given that the utility function is characterised by decreasing absolute risk aversion and decreasing absolute prudence, it holds that the difference in magnitudes between the left-hand side and the right-hand side of inequality of (28) as well as the inequality of (32) are higher in case of bad health status compared to good health status. Consequently, the decrease in consumption in period 1 (C_1) and the decrease in investment in the risky asset (x) is stronger for individuals with worse health.

B Tabulation of Deleted Observations

Table 5 shows the number of observations that were deleted due to missing information. The differences in starting observations for each subsample is due to unequal distribution of couple and single households. Further, as noted in Section 3, the consumption data considers the CAMS dataset, which is a subset of data from the HRS sample.

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 twelve HRS waves employed in this study, these numbers point to a similar (and actually slightly larger) deletion of observations. Most recently, Gábor-Tóth and Georgarakos (2018) 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, which points to a more drastic deletion of observations than needed for this study (with a total of 22,480 observations used for analysis of consumption). The sample reduction thus seems reasonable.

Table 5: Tabulation of Deleted Observations

		Consumption Sample		Financial Sample	
Deletion-criterion		Couple	Single	Couple	Single
Starting observations		12,950	12,236	132,961	56,914
Subj. health	-	21	11	117	50
Medical hist.	-	600	73	5,245	334
Hospital/Doctor	-	23	13	300	128
Insured	-	94	82	806	391
Education	-	0	0	28	7
Ethnicity	-	11	8	63	14
Durable spend. $\geq$ \$6000	-	31			
Durable spend. $\geq$ \$4000	-		33		
Stocks $\geq \$1,000,000$	-			2,025	
Stocks $\geq \$660,000$	-				899
Stocks > Total wealth	-			3,741	3,315
Household-observations > 1	-	661	1,046	3,968	3,560
Final observations	=	11,510	10,970	116,668	48,216

Monetary values are in 2010 Dollars.

C Further Notes on the Methodology

C.1 Anecdotal Evidence on Standard Errors

Table 6 presents fixed effect regression results with conventional (in parentheses) and household-level clustered standard errors (in brackets). As there do not seem to be substantive differences in standard errors, the assumption of the fixed effect and pooled Tobit model of no correlation between estimation errors does not seem to be violated to a concerning extent.

Table 6: Linear Fixed Effect Estimation Results

	(1)	(3)	(5)	(7)	(9)	(11)
	Couple	Single	Couple	Single	Couple	Single
	Durable consumption		Risky asset share		Safe asset share	
$\log(\text{HPU}_{12})$	-146.7***	-22.08	-0.007***	-0.013***	0.020***	0.023***
	(24.90)	(15.17)	(0.0014)	(0.002)	(0.002)	(0.003)
	[24.60]	[15.43]	[0.0015]	[0.002]	[0.002]	[0.003]
VIX_{12}	9.171***	1.362	0.002***	0.001***	-0.002***	-0.001***
	(3.035)	(1.815)	(0.0001)	(0.0002)	(0.0002)	(0.0003)
	[2.751]	[1.767]	[0.0001]	[0.0002]	[0.0002]	[0.0003]
SP500_{12}	-952.3	-863.0*	-0.079	-0.129	-0.227**	-0.036
	(797.5)	(524.3)	(0.077)	(0.112)	(0.099)	(0.144)
	[807.3]	[518.3]	[0.072]	[0.109]	[0.0936]	[0.138]
CEI_{12}	8,910	-527.2	4.103***	3.539***	-5.488***	-3.159**
	(8,552)	(5,091)	(0.736)	(1.096)	(0.954)	(1.416)
	[7,899]	[4,865]	[0.706]	[1.041]	[0.925]	[1.356]
2^{nd} Inc. Q.	-16.81	-8.653	0.007**	0.011***	0.006	-0.003
	(41.82)	(17.17)	(0.003)	(0.003)	(0.005)	(0.004)
	[34.11]	[16.60]	[0.003]	[0.003]	[0.005]	[0.004]
3^{rd} Inc. Q.	-60.67	21.60	0.016***	0.027***	0.009**	-0.010*
	(44.89)	(22.88)	(0.004)	(0.004)	(0.005)	(0.005)
	[39.57]	[24.57]	[0.003]	[0.005]	[0.005]	[0.006]
4^{th} Inc. Q.	0.962	34.04	0.027***	0.021***	0.018***	0.014**
	(48.49)	(31.09)	(0.004)	(0.005)	(0.005)	(0.007)
	[44.74]	[40.18]	[0.004]	[0.006]	[0.005]	[0.008]
2^{nd} Wealth Q.	77.70*	50.62***	0.027***	0.043***	-0.040***	-0.037***
	(41.53)	(19.61)	(0.004)	(0.004)	(0.005)	(0.005)
	[32.11]	[19.93]	[0.003]	[0.004]	[0.005]	[0.006]
3^{rd} Wealth Q.	138.0***	35.52	0.088***	0.093***	-0.070***	-0.063***
	(48.60)	(25.81)	(0.004)	(0.004)	(0.005)	(0.006)
	[43.68]	[27.50]	[0.004]	[0.006]	[0.006]	[0.007]
4^{th} Wealth Q.	141.7**	63.17*	0.190***	0.176***	-0.086***	-0.091***
	(55.70)	(33.23)	(0.004)	(0.005)	(0.006)	(0.007)
	[52.81]	[36.27]	[0.005]	[0.008]	[0.007]	[0.010]
Years ret.	-0.753	-0.283	0.0002	0.000	0.001***	0.0002
	(1.706)	(0.859)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
	[1.883]	[0.841]	[0.0001]	[0.0001]	[0.0002]	[0.0002]
Age	-1.106	-1.640	-0.003***	-0.0007***	0.001***	0.002***
	(3.799)	(2.418)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
	[3.794]	[2.387]	[0.0002]	[0.0003]	[0.0003]	[0.0004]
Constant	1,000***	393.1***	0.194***	0.127***	-0.547***	-0.480***
	(219.9)	(145.6)	(0.012)	(0.018)	(0.016)	(0.023)
	[209.3]	[144.5]	[0.014]	[0.022]	[0.020]	[0.031]
Households	2,675	2,706	20,529	10,469	20,529	10,469
Observations	11,510	10,970	116,668	48,216	116,668	48,216

*, ** and *** denote significance at 10%, 5%, 1%, respectively, as assessed by conventional standard errors in parentheses. Household-level clustured standard errors are in brackets. Time-invariant household variables are subsumed by the fixed effects.

C.2 Remark on Baker et al.'s (2016) Firm-Level Results

This section outlines a pitfall of the multiplicative-interaction model when used for causal inference on the effect of macroeconomic variables. The results of Baker et al. (2016) are used for illustrative purposes.

In Column (2) of Table 2, Baker et al. (2016) state the results of a regression of the form

$$y_{it} = \beta_1 \log(EPU_t) + \beta_2\big(\log(EPU_t) \times intensity_i\big) + X_{it}\beta_3 + \mu_i + \lambda_t + \varepsilon_{it}, \tag{33}$$

for $i = \{1, \ldots, N\}$ and $t = \{1, \ldots, T\}$. Notice that the coefficient β_1 is unidentified and is omitted from the estimation due to the time-fixed effect λ_t, with which $\log(EPU_t)$ is perfectly colinear[39]. Nevertheless, it holds that the complete marginal effect of policy uncertainty for firm i is given by $\frac{\beta_1}{EPU_t} + \frac{\beta_2 \times intensity_i}{EPU_t}$. (Irrespective of what can be estimated in the above regression framework.)

This is in contrast to the claim Baker et al. (2016) make in the paragraph corresponding to the result presented in column (2) of Table 2: "The coefficient of 0.215 [β_2] on the log(EPU) intensity measure suggests that for every 1% increase in our policy uncertainty index a firm with, say, a 50% government revenue share [the intensity measure] would see its stock volatility rise by 0.11%" (p. 1620).

However, the authors neglect the base-effect of policy uncertainty on firms (β_1), which is subsumed by the time-fixed effect (λ_t). The above statement is thus not correct. A complete interpretation of the result would be: "The coefficient of 0.215 on the log(EPU) intensity measure suggests that for every 1% increase in our policy uncertainty index a firm with, say, a 50% government revenue share [the intensity measure] would see its stock volatility rise by 0.11% *more than a firm with 0% government revenue share.*"

Note, however, that while we can compare the effect of policy uncertainty across firms with differing intensities, we cannot infer about the *magnitude or sign* of the total marginal effect of policy uncertainty of *any* firm without having an estimate of β_1. Because β_1 cannot be identified if time-fixed effects are included in the regression, a specification as in (33) does not allow for unequivocal conclusions on the effect of a macroeconomic variable such as EPU_t.

[39] The same does not hold for β_2, as the time-fixed effect is not perfectly colinear with $\log(EPU_t) \times intensity_i$.

C.3 EM Algorithm for Concomitant-Variable Latent Class Tobit Models

To the best of my knowledge, no version of the EM algorithm specifically for estimating concomitant-variable latent class Tobit models exist. While its derivation follows from other modifications – in particular Karlsson and Laitila (2014) and Van der Heijden et al. (1996), who develop a variant of the EM algorithm for concomitant-variable latent class models and finite mixture Tobit models, respectively – a description of the specific EM variant employed for this thesis might be useful; both for transparency of research and for interested readers. Additional details on the EM algorithm were taken from McLachlan and Peel (2004). The procedure is implemented in R, with code readily available upon request.

The EM algorithm is a suitable alternative for the estimation of mixture models including the latent class model employed in this study, as it overcomes the computational complexities of the likelihood in equation (8). The trick is to view the estimation problem as an incomplete data problem, where a vector of component labels for each observation exists – i.e., we assume the model specified in (7) is true –, but is unobserved. Let S_i be this missing component-membership vector, whose elements $s_{j,i}$ are binary indicators equal to 1 if y_i stems from mixture component j and 0 otherwise. Then, S_i are realised (unobserved) draws from the random vector $\tilde{S}_i$ with multinomial distribution consisting of one draw from M categories with probabilities $[\pi_{1,i}, \dots, \pi_{M,i}]$ that satisfy $\sum_{j=1}^{M} \pi_{j,i} = 1$. Assuming that we actually *do* observe component-membership, the *complete-data* log-likelihood is given by

$$\ell_C(\boldsymbol{\theta}) = \sum_{i=1}^{N} \sum_{j=1}^{M} s_{j,i} \Big(\log(\pi_{j,i}) + \log(f(y_i|X_i, \theta_j)) \Big), \tag{34}$$

where $f(y_i|X_i, \theta_j)$ is the Tobit density specified in equation (9), $\pi_{j,i}$ is the concomitant-variable prior probability specification given by equation (10) with arguments Z and parameters α, and $\boldsymbol{\theta}$ summarises all component specific coefficient vectors (θ_j) and the concomitant-variable coefficients (α). For notational convenience, the panel structure of the data is ignored; N denotes the total amount of observations. The EM algorithm then proceeds iteratively in two steps; an expectation step and a maximisation step (thus also the name). Below, I illustrate both steps as well as the initialisation of the algorithm, its convergence-criterion, and the standard error approximation.

E-Step. The expectation step requires the computation of the conditional expectation of the elements of the unobserved component label vector $\tilde{s}_{j,i}$ given the data y_i, X_i and Z_i. For iteration $(k+1)$, this is given in a Bayesian fashion by

$$\begin{aligned} E_{\boldsymbol{\theta}^{(k)}}\left[\tilde{s}_{j,i}|y_i, X_i, Z_i, \boldsymbol{\theta}^{(k)}\right] &= P_{\boldsymbol{\theta}^{(k)}}\left[\tilde{S}_i = j|y_i, X_i, Z_i, \boldsymbol{\theta}^{(k)}\right] \\ &= \frac{\pi_{j,i}^{(k)} f(y_i|X_i, \theta_j^{(k)})}{\sum_{m=1}^{M} \pi_{m,i}^{(k)} f(y_i|X_i, \theta_m^{(k)})} \\ &= \tau_{j,i}^{(k+1)} \end{aligned} \tag{35}$$

where $\tau_{j,i}^{(k+1)}$ is equivalent to the posterior component probability defined in equation (11) when using the coefficient estimate of the kth EM iteration.

M-Step. The maximisation step of the $(k+1)$th iteration requires the global maximisation of the conditional complete data likelihood with respect to the parameters $\boldsymbol{\theta}$ to obtain a new set of coefficient estimates to be used for the next iteration ($\boldsymbol{\theta}^{(k+1)}$). That is,

$$\begin{aligned} \max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta}^{(k)}) &= E_{\boldsymbol{\theta}^{(k)}}\left[\ell(\boldsymbol{\theta})|y, X, Z, \boldsymbol{\theta}^{(k)}\right] \\ &= \sum_{i=1}^{N}\sum_{j=1}^{M} \tau_{j,i}^{(k+1)}\Big(\log(\pi_{j,i}) + \log(f(y_i|X_i, \theta_j))\Big), \end{aligned} \tag{36}$$

where $\boldsymbol{\theta}$ summarises all component specific coefficient vectors (θ_j) and the concomitant-variable coefficients (α). The conditional likelihood can be split into $(M+1)$ parts that can be optimised independently. Namely, (36) is equivalent to

$$\begin{aligned} &\max_{\alpha} \sum_{i=1}^{N}\sum_{j=1}^{M} \tau_{j,i}^{(k+1)} \log(\pi_{j,i}) \\ =&\sum_{i=1}^{N}\sum_{j=1}^{M} \tau_{j,i}^{(k+1)} \log\Big(\frac{\exp\left(\alpha_{j,0} + Z_{it}\alpha_{j,1}\right)}{\sum_{m=1}^{M}\exp\left(\alpha_{m,0} + Z_{it}\alpha_{m,1}\right)}\Big) \end{aligned} \tag{37}$$

where the coefficients of component 1 are set to 0 for identification (i.e., $\alpha_{1,0} = 0$ and $\alpha_{1,1} = 0$), as well as

$$\begin{aligned} &\max_{\theta_j} \sum_{i=1}^{N} \tau_{j,i}^{(k+1)} \log(f(y_i|X_i, \theta_j)) \\ =&\sum_{i=1}^{N} \tau_{j,i}^{(k+1)} \log\Bigg(\Big(\Phi\big(\frac{-X_{it}\beta_j}{\sigma_j}\big)\Big)^{I[y_{it}=0]}\Big(\frac{1}{\sigma_j\sqrt{2\pi}}\exp\big(\frac{-1}{2\sigma_j^2}(y_{it} - X_{it}\beta_j)^2\big)\Big)^{I[y_{it}>0]}\Bigg) \\ &\text{for } j \in \{1, \ldots, M\}, \end{aligned} \tag{38}$$

where Φ denotes the normal CDF and I is an indicator function. As (37) and (38) are linear transformations of the multinomial logit log-likelihood and the Tobit log-likelihood, maximisation of the three independent parts can be done via conventional maximisation techniques[40]. This leads to a new set of coefficient estimates to be used in the next iteration's E-step.

Initialisation. To calculate the first E-step, an initial guess of the coefficient vector $\boldsymbol{\theta}^{(0)}$ is needed. McLachlan and Peel (2004) present several alternatives. While a grid search across various initial configurations of $\boldsymbol{\theta}^{(0)}$ seems ideal, this is computationally infeasible due to the high number of parameters considered in this study. Instead, I consider an alternative initialisation step through a random guess of the posterior probabilities. That is, $\tau_{j,i}^{(0)}$ are taken as random draws from a uniform distribution between 0.1 and 0.9. These are then considered in an pre-estimation M-step to arrive at an initial guess $\boldsymbol{\theta}^{(0)}$.

For each model, the EM algorithm is considered multiple times to avoid dependency on the specific starting value. This is particularly important as the EM algorithm has been shown to potentially lead to local rather than global maxima (e.g., McLachlan & Peel, 2004). Further, the likelihood of a finite mixture of Tobit models is not globally concave, giving further reason for

[40]In particular, I employ R's 'optim' function using the BFGS algorithm.

concern that the EM algorithm terminates in undesirable local maxima. Karlsson and Laitila (2014) suggest the use of several starting points in line with Wu (1983). Usually, 15 random starting values are considered to be a good norm (McLachlan & Peel, 2004), however, due to immense CPU times, I only consider 5 random starting points. The instance with the highest likelihood value is selected as the final result. For early results, the models were also estimated with more random starting values, however, as this had no substantial impact on the results and no impact on the conclusions, the restriction of 5 starting values seems reasonable.

Convergence criterion. McLachlan and Peel (2004) discuss various convergence criteria of the EM algorithm. One that seems to be commonly applied is that the procedure terminates once $L(\boldsymbol{\theta}^{(k+1)}) - L(\boldsymbol{\theta}^{(k)})$ changes by an arbitrarily small amount – that is, once the values of likelihood (defined in (8)) converge sufficiently. However, as Wu (1983) discusses, convergence of $L(\boldsymbol{\theta})$ does not necessarily imply convergence in $\boldsymbol{\theta}$. For this reason, I define the criterion on convergence of the coefficient vector explicitly. In particular, the EM algorithm employed in this study terminates when

$$\frac{\theta_j^{(k+1)} - \theta_j^{(k)}}{\theta_j^{(k)}} < 0.01 \quad \text{for all } j \in \{1, \dots, |\boldsymbol{\theta}|\} \tag{39}$$

That is, the EM algorithm terminates when the change in every coefficient between two iterations is smaller than 1%.

Standard errors. In contrast to maximum likelihood estimation, the EM algorithm does not provide standard errors as a by-product. Asymptotic standard errors could be computed using first and second order derivatives of the log-likelihood given by the log of equation (8). However, the second order derivatives are tedious to derive and cannot be readily approximated by conventional numerical methods implemented in R due to their complexity. One could simply calculate the outer-product of gradients estimation of the covariance matrix as the first order conditions are rather straightforward, however, this would only provide a lower bound on the standard errors Heij et al. (2004).

As an alternative, this study adapts McLachlan and Peel's (2004) finite mixture bootstrap procedure to the panel structure of the data in line with the panel bootstrap procedure outlined in Cameron and Trivedi (2005). In particular, a random subsample of 3000 households (rather than observations), each with equal probability, is drawn with replacement from the population in each bootstrap iteration. The concomitant-variable latent class Tobit model is then estimated on the bootstrap sample with the EM algorithm (which considers 5 sets of random starting values). The resulting coefficient estimate is denoted by $\hat{\boldsymbol{\theta}}_b$, where b denotes the bootstrap iteration.

The bootstrap coefficient estimate is then given by $\bar{\hat{\boldsymbol{\theta}}} = \sum_{b=1}^{B} \frac{\hat{\boldsymbol{\theta}}_b}{B}$, with corresponding covariance matrix given by $cov(\hat{\boldsymbol{\theta}}) = \sum_{b=1}^{B} \frac{(\hat{\boldsymbol{\theta}}_b - \bar{\hat{\boldsymbol{\theta}}})(\hat{\boldsymbol{\theta}}_b - \bar{\hat{\boldsymbol{\theta}}})^T}{B-1}$. For computational reasons, only 25 bootstrap iterations are considered despite existing literature's suggestions to set $B > 50$. To allow for bootstrapping standard errors despite potential label switching of the mixture model, the component coefficient vectors are ordered by variance in each bootstrap iteration as suggested by McLachlan and Peel (2004).

D Complete Estimation Results

D.1 Censored Fixed Effect and Pooled Tobit Model

Table 7: Complete Estimation Results – Couple Households

Couple Households	(1) Fixed effects	(2) Pooled	(3) Fixed effects	(4) Pooled	(5) Fixed effects	(6) Pooled
	Durable spending		Risky asset share		Safe asset share	
$\log(\mathrm{HPU}_{12})$	-343.5***	-121.6***	-0.019***	-0.058***	0.029***	0.009***
	(59.28)	(37.64)	(0.004)	(0.004)	(0.003)	(0.003)
VIX_{12}	20.45***	9.944*	0.004***	0.002***	-0.003***	-0.004***
	(6.740)	(5.822)	(0.0004)	(0.0004)	(0.0002)	(0.0003)
$\mathrm{SP500}_{12}$	-2,598	2,167	-0.270	-0.823***	-0.335**	-0.350*
	(1,994)	(1,444)	(0.191)	(0.220)	(0.140)	(0.192)
CEI_{12}	17,599	-537.7	9.154***	24.17***	-8.259***	-10.86***
	(18,862)	(17,047)	(1.925)	(2.094)	(1.380)	(1.827)
2^{nd} Inc. Q.	-50.69	61.08	0.056***	0.123***	0.012	-0.131***
	(104.1)	(70.96)	(0.016)	(0.011)	(0.010)	(0.008)
3^{rd} Inc. Q.	-152.5	191.8***	0.084***	0.209***	0.015	-0.196***
	(111.7)	(70.19)	(0.015)	(0.010)	(0.010)	(0.008)
4^{th} Inc. Q.	-15.91	483.0***	0.100***	0.252***	0.030***	-0.249***
	(119.0)	(73.53)	(0.016)	(0.011)	(0.010)	(0.008)
2^{nd} Wealth Q.	201.1**	174.0***	0.278***	0.237***	-0.121***	-0.304***
	(88.16)	(61.07)	(0.027)	(0.011)	(0.015)	(0.008)
3^{rd} Wealth Q.	347.8***	294.5***	0.525***	0.484***	-0.166***	-0.548***
	(114.2)	(61.01)	(0.027)	(0.011)	(0.015)	(0.008)
4^{th} Wealth Q.	361.5***	366.7***	0.741***	0.752***	-0.185***	-0.66***
	(133.7)	(63.65)	(0.027)	(0.011)	(0.016)	(0.008)
Years ret.	-2.512	1.097	0.001***	0.002***	0.002***	0.001***
	(4.894)	(2.341)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Age	-3.765	-18.77***	-0.007***	0.001***	0.002***	0.001***
	(9.264)	(2.280)	(0.001)	(0.0002)	(0.0004)	(0.0002)
Any children		202.8**		0.032***		-0.023***
		(92.13)		(0.010)		(0.009)
GED		342.1***		0.101***		-0.123***
		(87.13)		(0.011)		(0.009)
High school		189.6***		0.151***		-0.211***
		(57.12)		(0.007)		(0.005)
Some college		303.2***		0.188***		-0.266***
		(60.25)		(0.007)		(0.006)
Above college		383.3***		0.233***		-0.365***
		(62.57)		(0.007)		(0.006)
African Am.		-173.5***		-0.160***		0.235***
		(61.05)		(0.008)		(0.006)
Other ethn.		35.20		-0.091***		0.170***
		(81.14)		(0.011)		(0.009)
Constant		386.0*		-0.915***		0.573***
		(231.1)		(0.031)		(0.026)
Households	2,675	2,675	20,529	20,529	20,529	20,529
Observations	11,510	11,510	116,668	116,668	116,668	116,668
Share censored	0.57	0.57	0.63	0.63	0.36	0.36

*, ** and *** denote significance at 10%, 5%, 1% , respectively. Asymptotic standard errors are presented in parentheses. 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. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages. Time-invariant household variables are subsumed by the fixed effects.

Table 8: Complete Estimation Results – Single Households

Single Households	(1) Fixed effects	(2) Pooled	(3) Fixed effects	(4) Pooled	(5) Fixed effects	(6) Pooled
	Durable spending		Risky asset share		Safe asset share	
$\log(\mathrm{HPU}_{12})$	-73.10	6.656	-0.051***	-0.082***	0.052***	0.009
	(55.36)	(34.86)	(0.009)	(0.008)	(0.006)	(0.007)
VIX_{12}	3.990	1.815	0.003***	0.003***	-0.003***	-0.005***
	(6.338)	(5.428)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathrm{SP500}_{12}$	-3,399*	-436.4	-0.719*	-0.430	-0.112	-0.041
	(1,955)	(1,412)	(0.414)	(0.489)	(0.310)	(0.418)
CEI_{12}	-2,460	-7,436	12.63***	20.43***	-7.354**	-6.104
	(17,343)	(15,664)	(3.990)	(4.751)	(2.993)	(4.037)
2^{nd} Inc. Q.	-27.30	161.3***	0.040***	0.176***	-0.005	-0.173***
	(62.66)	(38.35)	(0.014)	(0.011)	(0.010)	(0.009)
3^{rd} Inc. Q.	48.15	345.6***	0.0761***	0.230***	-0.011	-0.215***
	(79.19)	(48.02)	(0.0153)	(0.0127)	(0.0112)	(0.0108)
4^{th} Inc. Q.	71.64	392.1***	0.051***	0.225***	0.031**	-0.220***
	(114.0)	(67.30)	(0.017)	(0.016)	(0.013)	(0.014)
2^{nd} Wealth Q.	186.1**	160.1***	0.379***	0.403***	-0.134***	-0.368***
	(73.58)	(40.79)	(0.027)	(0.015)	(0.018)	(0.011)
3^{rd} Wealth Q.	132.3	188.1***	0.552***	0.664***	-0.177***	-0.617***
	(100.5)	(46.05)	(0.028)	(0.015)	(0.020)	(0.011)
4^{th} Wealth Q.	213.0*	271.2***	0.721***	0.925***	-0.211***	-0.759***
	(125.8)	(52.59)	(0.029)	(0.017)	(0.021)	(0.013)
Years ret.	-1.711	-2.912*	0.0003	0.002***	0.0007	0.0002
	(3.733)	(1.724)	(0.001)	(0.0004)	(0.0005)	(0.0004)
Age	-5.290	-12.90***	-0.002*	0.003***	0.004***	0.006***
	(8.919)	(1.823)	(0.001)	(0.0005)	(0.001)	(0.0004)
Any children		113.6**		-0.035***		0.024**
		(46.36)		(0.012)		(0.010)
GED		19.62		0.111***		-0.114***
		(79.28)		(0.028)		(0.022)
High school		58.04		0.194***		-0.294***
		(44.40)		(0.013)		(0.011)
Some college		96.10**		0.280***		-0.379***
		(47.64)		(0.014)		(0.012)
Above college		265.1***		0.353***		-0.482***
		(55.43)		(0.015)		(0.013)
African Am.		-67.85*		-0.301***		0.319***
		(41.07)		(0.015)		(0.011)
Other ethn.		-3.679		-0.149***		0.149***
		(78.55)		(0.026)		(0.021)
Female		34.92		0.015		-0.003
		(37.32)		(0.010)		(0.008)
Constant		-357.5*		-1.217***		0.480***
		(197.0)		(0.059)		(0.050)
Households	2,706	2,706	10,469	10,469	10,469	10,469
Observations	10,970	10,970	48,216	48,216	48,216	48,216
Share censored	0.72	0.72	0.76	0.76	0.58	0.58

*, ** and *** denote significance at 10%, 5%, 1% , respectively. Asymptotic standard errors are presented in parentheses. 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. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages. Time-invariant household variables are subsumed by the fixed effects.

D.2 Concomitant-Variable Latent Class Tobit Model

Table 9: Complete Estimation Results

Couple Households	(1) Durable spending		(2) Risky asset share		(3) Safe asset share	
Prior Probability						
Constant		0.544		2.909***		0.682**
		(0.860)		(0.873)		(0.283)
Subj. health		-0.027		0.189***		0.286***
		(0.095)		(0.070)		(0.045)
Medical hist.		0.065		0.001		0.005
		(0.123)		(0.080)		(0.051)
Stroke/Heart att.		-0.084		-0.184		0.015
		(0.173)		(0.147)		(0.098)
Physical lim.		-0.025		-0.013		0.084***
		(0.063)		(0.022)		(0.013)
Hospital/Doctor		0.493		-0.472		-0.610***
		(0.573)		(0.609)		(0.213)
Insured		0.017		-0.469**		-0.481***
		(0.238)		(0.203)		(0.125)
Components	*C.1*	*C.2*	*C.1*	*C.2*	*C.1*	*C.2*
log(HPU_{12})	205.1	-384.8**	0.000	-0.059***	-0.001	0.028**
	(378.3)	(187.9)	(0.015)	(0.008)	(0.002)	(0.011)
VIX_{12}	3.005	16.42	0.002*	0.001	-0.001***	-0.002**
	(20.98)	(17.18)	(0.001)	(0.001)	(0.000)	(0.001)
$SP500_{12}$	2,078	-902.1	-0.223	-0.792**	0.007	-0.315
	(11,699)	(6,253)	(0.710)	(0.383)	(0.140)	(0.754)
CEI_{12}	2,872	-3,206	6.627	23.87***	-0.834	-11.81*
	(63,887)	(49,490)	(5.542)	(5.870)	(1.322)	(6.362)
2^{nd} Inc. Q.	94.44	-30.87	-0.004	0.129***	0.004	-0.189***
	(91.82)	(210.4)	(0.038)	(0.038)	(0.006)	(0.030)
3^{rd} Inc. Q.	151.7	117.2	-0.016	0.219***	0.018**	-0.270***
	(161.8)	(247.1)	(0.038)	(0.035)	(0.007)	(0.032)
4^{th} Inc. Q.	40.44	692.0***	-0.029	0.265***	0.026***	-0.345***
	(211.8)	(171.6)	(0.042)	(0.039)	(0.006)	(0.033)
2^{nd} Wealth Q.	85.47	295.8	0.012	0.209***	-0.428	-0.116
	(150.6)	(187.24)	(0.163)	(0.042)	(0.650)	(0.280)
3^{rd} Wealth Q.	12.42	600.9**	0.055	0.447***	-0.425	-0.431
	(184.4)	(293.7)	(0.277)	(0.045)	(0.649)	(0.276)
4^{th} Wealth Q.	38.31	737.8**	0.049	0.695***	-0.434	-0.585**
	(206.7)	(303.5)	(0.488)	(0.082)	(0.649)	(0.271)

Continued on next page.

Table 9: Complete Estimation Results (Continued)

Continued from previous page.						
Years ret.	3.079	-0.652	0.000	0.001	0.000	0.000
	(4.307)	(4.838)	(0.001)	(0.001)	(0.000)	(0.001)
Age	-7.177	-27.25***	0.000	0.001	0.000	-0.001
	(4.500)	(4.969)	(0.001)	(0.001)	(0.001)	(0.001)
Any children	-34.35	777.0	0.104	0.001	0.002	-0.010
	(365.3)	(1,902)	(0.298)	(0.047)	(0.009)	(0.044)
GED	-52.53	662.4**	-0.032	0.095	-0.006	-0.107**
	(195.9)	(260.6)	(0.316)	(0.080)	(0.017)	(0.043)
High school	78.24	339.2**	0.020	0.147***	-0.009	-0.184***
	(110.3)	(157.4)	(0.021)	(0.040)	(0.007)	(0.032)
Some college	99.22	499.6***	0.023	0.189***	-0.017**	-0.231***
	(164.0)	(187.1)	(0.030)	(0.042)	(0.008)	(0.034)
Above college	51.34	654.7***	0.008	0.237***	-0.023***	-0.330***
	(160.7)	(179.2)	(0.029)	(0.040)	(0.007)	(0.036)
African Am.	-89.94	-270.2*	0.015	-0.189***	0.047	0.237**
	(133.0)	(146.1)	(0.029)	(0.040)	(0.268)	(0.114)
Other ethn.	-71.14	71.41	-0.013	-0.093***	0.013	0.185***
	(147.0)	(170.0)	(0.072)	(0.035)	(0.010)	(0.044)
Constant	-658.7	964.6	0.553	-0.899***	-0.462	0.771**
	(1,689)	(1,783)	(0.615)	(0.092)	(0.656)	(0.317)
Component size	0.28	0.72	0.07	0.93	0.32	0.68
Log-likelihood		-46,832.3		-64,048.2		-61,712.2
Observations		11,510		116,668		116,668

Estimates are calculated using the EM algorithm illustrated in Appendix C. Bootstrapped standard errors are in parentheses. *, ** and *** denote significance at 10%, 5%, 1% , respectively. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages. 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.

D.3 Tobit Model-Based Recursive Partitioning

Table 10: Complete Estimation Results – Risky Asset Share (Nodes 1-9)

Couple households	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(HPU_{12})	-0.200***	-0.092	-0.059**	0.073	-0.051***	-0.116***	-0.031***	-0.144***	-0.056***
	(0.069)	(0.070)	(0.024)	(0.046)	(0.010)	(0.013)	(0.012)	(0.048)	(0.009)
VIX_{12}	0.006	0.003	-0.003	-0.003	-0.0004	0.0003	0.001	-0.011*	0.002**
	(0.006)	(0.008)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)
$SP500_{12}$	-5.492	1.112	1.684	3.779**	-1.067*	-0.722	-1.696***	-6.993**	-1.240**
	(3.542)	(5.317)	(1.279)	(1.823)	(0.593)	(0.750)	(0.658)	(3.539)	(0.482)
CEI_{12}	-26.45	-5.160	-19.63	-0.401	26.15***	22.31***	26.52***	95.42***	38.81***
	(28.39)	(49.32)	(12.26)	(17.32)	(5.790)	(7.100)	(6.045)	(33.52)	(4.694)
2^{nd} Inc. Q.	-0.158	0.377	0.082	0.627***	0.129***	0.139***	0.091**	0.110	0.182***
	(0.131)	(0.235)	(0.096)	(0.137)	(0.045)	(0.048)	(0.038)	(0.140)	(0.028)
3^{rd} Inc. Q.	-0.073	0.170	0.178**	0.384***	0.191***	0.183***	0.158***	-0.013	0.253***
	(0.119)	(0.220)	(0.086)	(0.124)	(0.042)	(0.046)	(0.037)	(0.141)	(0.027)
4^{th} Inc. Q.	-0.196	0.382*	0.204**	0.369***	0.194***	0.219***	0.198***	-0.034	0.285***
	(0.119)	(0.222)	(0.083)	(0.121)	(0.042)	(0.046)	(0.037)	(0.143)	(0.027)
2^{nd} Wealth Q.	0.126	-0.306*	0.089	1.817	0.219***	0.293***	0.172***	2.213	0.216***
	(0.169)	(0.180)	(0.094)	(37.81)	(0.047)	(0.060)	(0.038)	(243.8)	(0.026)
3^{rd} Wealth Q.	0.507***	-0.367**	0.333***	2.150	0.454***	0.530***	0.373***	2.423	0.464***
	(0.161)	(0.169)	(0.089)	(37.81)	(0.045)	(0.058)	(0.037)	(243.8)	(0.026)
4^{th} Wealth Q.	0.871***	0.167	0.558***	2.451	0.727***	0.780***	0.607***	2.629	0.725***
	(0.163)	(0.159)	(0.088)	(37.81)	(0.045)	(0.058)	(0.037)	(243.800)	(0.026)
Years ret.	-0.003	-0.001	0.003	0.004	0.004***	0.003**	0.001*	-0.006*	0.002***
	(0.006)	(0.005)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Age	-0.005	0.017***	-0.003	-0.009***	-0.001	0.001	-0.001	0.016***	0.001
	(0.004)	(0.006)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
Any children	0.014	0.777***	-0.024	0.180**	0.095***	-0.005	0.016	-0.406**	0.011
	(0.169)	(0.222)	(0.041)	(0.079)	(0.027)	(0.036)	(0.028)	(0.195)	(0.022)
GED	0.094	1.130***	-0.161	-0.225	0.069	-0.041	0.075**	0.063	0.148***
	(0.188)	(0.297)	(0.117)	(0.137)	(0.042)	(0.050)	(0.036)	(0.209)	(0.026)
High school	0.273***	0.360*	-0.081	-0.029	0.043*	0.116***	0.103***	0.154	0.149***
	(0.094)	(0.199)	(0.076)	(0.082)	(0.026)	(0.031)	(0.022)	(0.098)	(0.015)
Some college	0.366***	0.519**	-0.046	0.000	0.031	0.094***	0.141***	0.167*	0.191***
	(0.010)	(0.202)	(0.075)	(0.081)	(0.026)	(0.031)	(0.023)	(0.100)	(0.016)
Above college	0.412***	0.508**	-0.032	0.080	0.103***	0.141***	0.143***	0.170*	0.228***
	(0.104)	(0.199)	(0.074)	(0.079)	(0.026)	(0.031)	(0.023)	(0.101)	(0.016)
African Am.	-0.347	-1.998	-0.145**	0.038	-0.150***	-0.108***	-0.182***	-2.267	-0.125***
	(0.212)	(61.78)	(0.071)	(0.146)	(0.027)	(0.035)	(0.028)	(237.5)	(0.016)
Other ethn.	0.149	0.275	-0.019	0.157	-0.006	-0.085*	-0.096***	-2.404	-0.076***
	(0.120)	(0.187)	(0.062)	(0.102)	(0.027)	(0.048)	(0.037)	(509.3)	(0.021)
Constant	0.273	-2.319***	0.030	-2.550	-0.637***	-0.465***	-0.604***	-2.527	-0.950***
	(0.473)	(0.618)	(0.221)	(37.81)	(0.101)	(0.123)	(0.097)	(243.8)	(0.075)
Observations	665	264	1,916	733	10,054	6,798	10,642	393	22,310

*, ** and *** denote significance at 10%, 5%, 1% , respectively. Asymptotic standard errors are presented in parentheses. 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. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages.

Table 11: Complete Estimation Results – Risky Asset Share (Nodes 10-21)

Couple households	(10)	(11)	(12)	(13)	(14)	(16)	(16)	(17)	(18)	(19)	(20)	(21)
log(HPU_{12})	-0.086***	-0.103***	0.065***	-0.161***	0.126**	-0.031	-0.048***	-0.005	0.017	-0.035*	-0.016	-0.058***
	(0.012)	(0.013)	(0.022)	(0.041)	(0.062)	(0.125)	(0.016)	(0.031)	(0.038)	(0.021)	(0.042)	(0.014)
VIX_{12}	0.009***	0.007***	0.008***	0.009**	0.007	0.036***	0.003*	-0.004	-0.007*	0.002	0.004	0.002
	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)	(0.012)	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.001)
$SP500_{12}$	0.577	-3.983***	-4.348***	-1.120	3.589	-1.716	-0.532	0.795	6.239***	1.968	1.203	0.932
	(0.674)	(0.824)	(1.227)	(2.387)	(3.077)	(6.091)	(0.937)	(1.987)	(1.986)	(1.257)	(2.729)	(0.897)
CEI_{12}	18.08***	39.66***	69.72***	40.24*	67.38***	-35.74	9.053	30.05	-44.78**	-6.569	22.18	5.092
	(6.531)	(7.700)	(11.83)	(23.24)	(24.97)	(54.27)	(8.990)	(19.66)	(18.65)	(12.33)	(26.30)	(8.548)
2^{nd} Inc. Q.	0.208***	0.069*	0.185***	0.232**	0.158*	-0.198	0.098**	0.231***	0.015	-0.120***	0.024	0.180***
	(0.036)	(0.036)	(0.058)	(0.096)	(0.086)	(0.175)	(0.042)	(0.074)	(0.055)	(0.045)	(0.094)	(0.032)
3^{rd} Inc. Q.	0.277***	0.143***	0.338***	0.358***	0.244***	-0.083	0.196***	0.292***	0.128**	-0.001	0.223**	0.292***
	(0.035)	(0.036)	(0.057)	(0.094)	(0.082)	(0.170)	(0.041)	(0.073)	(0.053)	(0.044)	(0.093)	(0.033)
4^{th} Inc. Q.	0.351***	0.219***	0.388***	0.367***	0.298***	0.178	0.239***	0.388***	0.193***	-0.012	0.132	0.346***
	(0.035)	(0.037)	(0.058)	(0.098)	(0.082)	(0.185)	(0.042)	(0.077)	(0.055)	(0.048)	(0.104)	(0.035)
2^{nd} Wealth Q.	0.186***	0.221***	0.206***	0.278***	0.411***	0.366*	0.235***	0.144*	0.182***	0.351***	0.133	0.342***
	(0.036)	(0.040)	(0.058)	(0.100)	(0.085)	(0.215)	(0.043)	(0.085)	(0.058)	(0.057)	(0.098)	(0.037)
3^{rd} Wealth Q.	0.431***	0.426***	0.478***	0.581***	0.684***	0.563**	0.444***	0.509***	0.448***	0.663***	0.402***	0.607***
	(0.035)	(0.039)	(0.056)	(0.099)	(0.085)	(0.226)	(0.042)	(0.082)	(0.058)	(0.057)	(0.097)	(0.036)
4^{th} Wealth Q.	0.658***	0.713***	0.809***	0.830***	0.876***	1.161***	0.706***	0.892***	0.714***	0.946***	0.733***	0.924***
	(0.036)	(0.040)	(0.058)	(0.103)	(0.086)	(0.240)	(0.043)	(0.085)	(0.061)	(0.060)	(0.102)	(0.038)
Years ret.	0.001**	0.001**	0.001	0.001	0.007**	-0.022**	0.002**	-0.001	0.001	0.002*	0.004*	0.002***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.008)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Age	0.002**	0.005***	0.001	0.003	-0.003	0.013**	0.002	0.008***	-0.001	0.002*	0.001	0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Any children	0.037	0.102***	-0.020	0.098	-0.017	3.138	0.031	-0.022	0.209**	0.024	-0.171*	0.062
	(0.034)	(0.037)	(0.056)	(0.093)	(0.073)	(89.44)	(0.042)	(0.083)	(0.086)	(0.051)	(0.098)	(0.039)
GED	0.114***	0.131***	0.094*	-0.127	0.136**	0.051	0.213***	0.106	0.046	0.209***	0.191*	-0.003
	(0.034)	(0.039)	(0.055)	(0.115)	(0.067)	(0.224)	(0.041)	(0.089)	(0.063)	(0.055)	(0.107)	(0.038)
High school	0.154***	0.143***	0.149***	0.136**	0.181***	0.058	0.241***	0.154***	0.115***	0.262***	0.182***	0.123***
	(0.020)	(0.023)	(0.034)	(0.062)	(0.042)	(0.128)	(0.026)	(0.049)	(0.038)	(0.033)	(0.065)	(0.021)
Some college	0.162***	0.230***	0.190***	0.225***	0.243***	0.160	0.251***	0.227***	0.193***	0.302***	0.252***	0.220***
	(0.022)	(0.024)	(0.036)	(0.067)	(0.047)	(0.148)	(0.028)	(0.054)	(0.042)	(0.037)	(0.072)	(0.023)
Above college	0.236***	0.221***	0.251***	0.223***	0.331***	0.279	0.383***	0.293***	0.275***	0.470***	0.348***	0.179***
	(0.022)	(0.024)	(0.038)	(0.069)	(0.050)	(0.173)	(0.030)	(0.056)	(0.047)	(0.039)	(0.079)	(0.026)
African Am.	-0.177***	-0.169***	-0.126***	-0.120	-0.070	-0.095	-0.172***	-0.020	-0.212***	-0.287***	-0.165	-0.207***
	(0.025)	(0.028)	(0.041)	(0.077)	(0.048)	(0.161)	(0.031)	(0.057)	(0.052)	(0.045)	(0.106)	(0.033)
Other ethn.	-0.123***	-0.206***	-0.196***	0.273***	-0.050	-0.019	-0.216***	-0.045	-0.070	-0.040	-0.125	-0.222***
	(0.034)	(0.047)	(0.062)	(0.094)	(0.085)	(0.217)	(0.050)	(0.101)	(0.075)	(0.071)	(0.158)	(0.059)
Constant	-1.004***	-1.073***	-1.812***	-1.022***	-2.032***	-5.328	-1.104***	-1.820***	-0.995***	-1.249***	-1.075***	-1.477***
	(0.103)	(0.108)	(0.191)	(0.321)	(0.377)	(89.45)	(0.132)	(0.251)	(0.251)	(0.165)	(0.321)	(0.111)
Observations	11,164	9,727	5,100	1,244	2,772	423	8,013	2,352	3,129	5,746	1,369	11,854

Table 12: Complete Estimation Results – Safe Asset Share (Nodes 1-6)

Couple households	(1)	(2)	(3)	(4)	(5)	(6)
log(HPU_{12})	0.034	-0.007	0.034***	0.012**	0.011	0.070
	(0.066)	(0.008)	(0.008)	(0.006)	(0.017)	(0.059)
VIX_{12}	0.004	-0.001	-0.004***	-0.003***	0.0003	-0.014**
	(0.007)	(0.001)	(0.001)	(0.001)	(0.002)	(0.007)
$SP500_{12}$	6.306*	-0.420	-0.233	0.250	0.184	1.368
	(3.511)	(0.449)	(0.453)	(0.357)	(0.961)	(3.774)
CEI_{12}	30.79	-7.147	-11.01**	-12.18***	-31.22***	-28.19
	(30.44)	(4.348)	(4.335)	(3.407)	(9.375)	(34.89)
2^{nd} Inc. Q.	-0.192	-0.007	-0.102***	-0.145***	-0.112***	-0.412***
	(0.151)	(0.031)	(0.027)	(0.019)	(0.039)	(0.109)
3^{rd} Inc. Q.	-0.433***	-0.047	-0.101***	-0.172***	-0.182***	-0.413***
	(0.142)	(0.029)	(0.025)	(0.018)	(0.039)	(0.117)
4^{th} Inc. Q.	-0.273*	-0.065**	-0.112***	-0.217***	-0.269***	-0.574***
	(0.143)	(0.029)	(0.025)	(0.018)	(0.040)	(0.137)
2^{nd} Wealth Q.	-0.511***	-0.137***	-0.279***	-0.291***	-0.332***	-0.172
	(0.165)	(0.026)	(0.027)	(0.017)	(0.037)	(0.120)
3^{rd} Wealth Q.	-0.741***	-0.355***	-0.477***	-0.495***	-0.541***	-0.570***
	(0.156)	(0.025)	(0.026)	(0.016)	(0.037)	(0.119)
4^{th} Wealth Q.	-1.063***	-0.453***	-0.571***	-0.583***	-0.644***	-0.523***
	(0.160)	(0.025)	(0.026)	(0.017)	(0.038)	(0.129)
Years ret.	0.022***	0.000	0.0002	0.0001	-0.0003	-0.001
	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Age	-0.010**	-0.001**	0.0003	-0.001	-0.001	-0.023***
	(0.004)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.004)
Any children	-0.123	-0.016	-0.047**	-0.005	0.036	-0.092
	(0.215)	(0.019)	(0.022)	(0.017)	(0.043)	(0.207)
GED	-0.296	-0.086***	0.005	-0.135***	-0.176***	-0.350**
	(0.204)	(0.032)	(0.028)	(0.018)	(0.046)	(0.172)
High school	-0.321***	-0.153***	-0.131***	-0.192***	-0.256***	-0.334***
	(0.105)	(0.020)	(0.018)	(0.011)	(0.025)	(0.086)
Some college	-0.282***	-0.194***	-0.185***	-0.243***	-0.290***	-0.453***
	(0.108)	(0.020)	(0.018)	(0.012)	(0.028)	(0.097)
Above college	-0.489***	-0.276***	-0.264***	-0.346***	-0.375***	-0.482***
	(0.118)	(0.019)	(0.018)	(0.012)	(0.030)	(0.112)
African Am.	0.001	0.250***	0.301***	0.263***	0.132***	-0.018
	(0.148)	(0.019)	(0.021)	(0.012)	(0.026)	(0.104)
Other ethn.	0.147	0.120***	0.195***	0.167***	0.185***	0.059
	(0.141)	(0.021)	(0.028)	(0.017)	(0.038)	(0.137)
Constant	1.442***	0.213***	0.174**	0.507***	0.655***	2.779***
	(0.544)	(0.071)	(0.070)	(0.052)	(0.136)	(0.485)
Observations	401	12,202	12,271	29,091	5,423	656

*, ** and *** denote significance at 10%, 5%, 1% , respectively. Asymptotic standard errors are presented in parentheses. 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. HPU and VIX denote Baker et al.'s (2016) health care policy uncertainty index and the Implied Volatility Index, respectively, matched to the final interview month of the HRS-respondent. SP500 and CEI denote growth rates of the S&P 500 Index and the Conference Board's Coincident Economic Indicator. Subscripts denote 12-month averages.

Table 13: Complete Estimation Results – Safe Asset Share (Nodes 7-13)

Couple households	(7)	(8)	(9)	(10)	(11)	(12)
log(HPU_{12})	-0.070***	0.055	0.244***	0.068	0.022***	-0.023***
	(0.024)	(0.035)	(0.053)	(0.072)	(0.008)	(0.009)
VIX_{12}	-0.002	-0.013***	-0.027***	-0.015*	-0.005***	-0.004***
	(0.003)	(0.004)	(0.006)	(0.009)	(0.001)	(0.001)
$SP500_{12}$	-0.510	-3.822*	6.387**	-0.255	-1.213**	-0.735
	(1.420)	(1.967)	(2.933)	(5.216)	(0.483)	(0.541)
CEI_{12}	3.242	-12.63	-33.77	27.06	-9.253**	-4.308
	(13.73)	(19.88)	(28.51)	(46.76)	(4.466)	(5.172)
2^{nd} Inc. Q.	-0.048	-0.298***	-0.540***	-0.242	-0.025	-0.157***
	(0.054)	(0.078)	(0.122)	(0.149)	(0.020)	(0.017)
3^{rd} Inc. Q.	-0.122**	-0.344***	-0.603***	-0.411***	-0.091***	-0.239***
	(0.053)	(0.077)	(0.124)	(0.148)	(0.020)	(0.017)
4^{th} Inc. Q.	-0.143**	-0.373***	-0.536***	-0.475***	-0.165***	-0.318***
	(0.057)	(0.080)	(0.135)	(0.172)	(0.020)	(0.019)
2^{nd} Wealth Q.	-0.362***	-0.453***	-0.467***	0.100	-0.245***	-0.362***
	(0.062)	(0.086)	(0.103)	(0.130)	(0.019)	(0.017)
3^{rd} Wealth Q.	-0.695***	-0.721***	-0.529***	-0.054	-0.464***	-0.647***
	(0.062)	(0.085)	(0.105)	(0.136)	(0.018)	(0.018)
4^{th} Wealth Q.	-0.824***	-0.815***	-0.839***	-0.312**	-0.577***	-0.799***
	(0.064)	(0.088)	(0.115)	(0.140)	(0.019)	(0.019)
Years ret.	-0.001	-0.0004	-0.000	0.004	0.001	0.0003
	(0.002)	(0.002)	(0.003)	(0.004)	(0.001)	(0.001)
Age	0.006***	-0.001	-0.004	-0.004	0.0001	0.003***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.0005)	(0.001)
Any children	-0.147*	0.058	0.190	-0.251*	-0.043**	-0.027
	(0.078)	(0.072)	(0.171)	(0.136)	(0.020)	(0.023)
GED	-0.106*	-0.141*	0.013	-0.238	-0.076***	-0.146***
	(0.064)	(0.083)	(0.120)	(0.176)	(0.021)	(0.020)
High school	-0.100***	-0.180***	-0.010	0.022	-0.183***	-0.224***
	(0.036)	(0.052)	(0.075)	(0.100)	(0.012)	(0.012)
Some college	-0.164***	-0.297***	-0.182**	-0.137	-0.228***	-0.292***
	(0.040)	(0.056)	(0.083)	(0.117)	(0.013)	(0.014)
Above college	-0.174***	-0.254***	-0.138	0.011	-0.312***	-0.419***
	(0.043)	(0.061)	(0.097)	(0.121)	(0.014)	(0.016)
African Am.	0.281***	0.411***	-0.055	0.302**	0.206***	0.224***
	(0.045)	(0.077)	(0.109)	(0.142)	(0.015)	(0.016)
Other ethn.	0.096	0.224***	0.104	0.203	0.170***	0.177***
	(0.064)	(0.083)	(0.179)	(0.228)	(0.024)	(0.026)
Constant	0.650***	0.928***	0.537	0.645	0.409***	0.905***
	(0.197)	(0.258)	(0.426)	(0.561)	(0.061)	(0.066)
Observations	2,750	1,196	655	290	21,912	26,681

Footnotes identical to Table 12.

E Remark on the Replication of Baker et al. (2016)

This section provides a brief explanations of the reasons for not explicitly reproducing the empirical results of Baker et al. (2016) in this thesis.

First, while Baker et al. (2016) investigate the effect of (general) economic policy uncertainty on *firms*' investment and employment decisions, this study analyses the effect of health care policy uncertainty on *households*' consumption and portfolio choice. Therefore, the explicit results of Baker et al. (2016) on firms are not relevant to this study and their reproduction would not add to answering the research question at hand.

Second, I assume that the reproduction of the explicit results of the reference paper are also meant as a challenge to the student writing the thesis. While this is certainly the case for many reference papers, it does not apply to the work of Baker et al. (2016) as complete Stata .do-files and corresponding data sets are readily accessible under the link '`http://www.policyuncertainty.com/research.html`'. The reproduction in this case does therefore not provide an additional challenge that would pose methodological difficulties.

Third, despite not explicitly reproducing the numerical results, I spent much time analysing the methodological approach that Baker et al. (2016) employ in their study. As noted in Section 4.2, I adapt a similar line of reasoning by exploiting variation in exposure to policy uncertainty. Further, I explicitly discuss the shortcomings of the multiplicative-interaction specification they employ, and point out a seemingly consequential pitfall of their methodology in Appendix C.2. It is my hope that this alleviates any concerns that I did not spent sufficient time on the methodology of Baker et al. (2016).

In consultation with Professor Lumsdaine, the empirical results of the reference paper were not reproduced in this thesis for the reasons named above.