Health Care Policy Uncertainty and its Effect on Households' Consumption and Portfolio Choice

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Introduction

Motivation:

- Health care is a central topic of policy debate
- HC reform is 2nd largest source of policy uncertainty in recent years in the US, behind fiscal policy (Baker et al., 2016)
- Medical expenditures increasing proportion of households' spending

For households, health care policy uncertainty is uncertainty about future spending needs

- Similar to uncertainty about future income
  (both affect consumption ability)

Previous literature

Households likely react to policy uncertainty along two dimensions:

- Consumption / Precautionary savings
  - Buffer-stock models (Zeldes, 1989; Kimball, 1990; Carroll, 1997)
- Portfolio Choice
  - Policy uncertainty as a background risk
  - Decreased willingness to endure other types of risk (Pratt and Zeckhauser, 1987; Kimball, 1993; Gollier and Pratt, 1996)

In times of policy uncertainty:

- Households save more (Giavazzi and McMahon, 2012; Aaberge et al., 2017)
- Households hold less risky portfolios (Delavande and Rohwedder, 2011; Agarwal et al., 2018; Gábor-Tóth and Georgarakos, 2018)

This paper

Two key questions:

- Does health care policy uncertainty affect households' economic behavior?
- Does the health care policy uncertainty-effect vary with households' health?

To answer the two key questions, this paper

- develops a simple two-period consumption and portfolio choice model to theoretically illustrate the potential health care policy uncertainty effect
- introduces econometric improvements
  - fixed effect censored regression of Honoré (1992) to account for pileups at zero and 100
  - model-based recursive partitioning procedure of Zeileis et al. (2008) and latent class model with parametrized component probabilities to flexibly analyze heterogeneous effects

Key implications of model

- *Proposition 1*
  Households decrease spending and relative investment in risky assets when faced with uncertainty about future costs of health care.

- *Proposition 2*
  Households in worse health decrease their spending and relative demand for risky assets more severely when faced with uncertainty about future health care costs.

First key question

Does health care policy uncertainty affect households' economic behavior?

Household data

- Unit of analysis is households
  - Analyze couples and singles separately
- RAND versions of:
  - Waves 2-12 of Health and Retirement Study (HRS; 1994-2014)
  - Consumption and Activities Mail Survey waves 1-8 (CAMS; 2001-2015)
- Gateway to Aging Harmonized HRS data for additional household variables

Analysis sample:

- 42,786 single and 54,717 couple household-wave observations (HRS only)
- 12,116 single and 7,862 couple household-wave observations (HRS including CAMS)

Household data (2/2)

Portfolio choice and financial variables:

- Follow Rosen and Wu (2004) and define four categories:
  - safe assets, risky assets, bonds, IRA retirement accounts
- Focus on shares of risky and safe assets over total financial wealth

Consumption and spending:

- Total spending

Additional controls:

- Age, education, income and wealth quartiles, retirement status and years in retirement, presence of living children, race, and gender (for single households)

Health care policy uncertainty index

Baker, Bloom, and Davis (2016) develop a computer-driven, news-based policy uncertainty index

- Based on the number of occurrences of articles with word triples "uncertain", "economic", and "policy" (and their synonyms) in ten major US newspapers
- Widely used to assess effect of policy uncertainty on firms (e.g., Gulen and Ion, 2015), macroeconomic tendencies (e.g., Stock and Watson, 2012)

Health care policy uncertainty index (Baker et al., 2016)

- Based on number of occurrences of word triplet *plus* a word related to health care (e.g., "Medicaid", "health insurance", "Obamacare")
- We merge the 12-month average preceding the month of interview with the HH data

Identification challenge: potential confoundedness with other macro sources of uncertainty (Bloom, 2014)

- Include 12-month averages of the SP500 growth rate and the VIX, as well as the Conference Board's Coincident Indicator

Health care policy uncertainty index

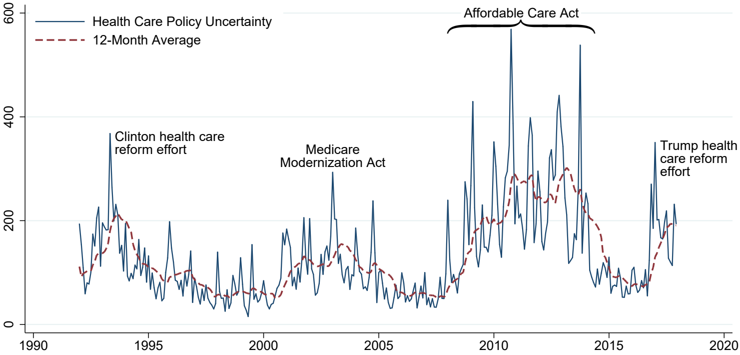

Figure 1: Health Care Policy Uncertainty Index 1992 – 2017

Source. Baker et al. (2016) and authors' calculations.

Methodology (Proposition 1)

Challenge: Households' risky asset share are concentrated at zero and safe asset share is concentrated at one

- Common solution is to use a Tobit model
  - Random effects: consistency of results depends on assumption that unobserved heterogeneity is uncorrelated with the covariates
  - Fixed effects: inconsistent when estimated via ML due to the incidental parameter problem (Honoré, 1992; Greene, 2004)
- Apply censored fixed effect model of Honoré (1992)
  - Controls for time-varying household-level controls, time-invariant unobserved heterogeneity, and potentially confounding economic uncertainty (via macro-level controls)
  - Errors may be heteroskedastic across households but assumed not to be autocorrelated
- Also use a pooled Tobit model for easier interpretation of results
  - Marginal effects need to be computed

Results (Proposition 1)

Proposition 1:
Households decrease spending and relative investment in risky assets when faced with uncertainty about future costs of health care.

Main results:

- Households decrease share in risky financial assets by 1-2 percentage points when faced with increase in health care policy uncertainty similar to that seen from 2016-17
- Couple households decrease total spending by 2.73% when faced with a health care policy uncertainty increase similar to 2016-2017; no analogous significant effect for single households

- Coefficients on controls are intuitive
  - Total spending, share in risky (safe) assets is monotonically increasing (decreasing) with income, wealth, education
  - Investment share in risky (safe) assets decreases (increases) with age

Second key question

Does the health care policy uncertainty-effect on households' economic behavior vary with households' health?

Does this effect vary with households' health?

Motivation:

1. Identification challenge: Causal interpretation requires policy uncertainty exposure to be unconfounded with exposure to other forms of uncertainty (e.g., general economic uncertainty)
   - Variation in households' health may be suitable for capturing uncertainty exposure across households
   - Particularly appropriate for HRS population: health of older Americans is unlikely to affect their *responsiveness* to general economic uncertainty
2. Bridge between policy uncertainty and literature in health economics
   - Evidence that health risk has a negative effect on demand for risky assets (Rosen and Wu, 2004; Berkowitz and Qiu, 2006; Edwards, 2008)
   - Evidence there is little or no effect (Fan and Zhao, 2009; Love and Smith, 2010)
   - Related papers on medical expenditure risk (Gruber and Yelowitz, 1999; Atella et al., 2004; Goldman and Maestas, 2013)

Does this effect vary with households' health?

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Health and health care utilization data

From the HRS data we use:

- Self-assessed health
- Severe conditions
- ADLs and IADLs
- Mobility
- Uninsured (1 if yes)
- Number of nights spent in a hospital

Methodology (Proposition 2)

Standard heterogeneous effects model usually involves a multiplicative-interaction specification such as

$$y_{it} = \beta_{i0} + \beta_1 \mathrm{PU}_t + \beta_2 \mathrm{PU}_t z_{it} + X_{it}\beta_3 + \varepsilon_{it} \tag{1}$$

- Hainmueller et al. (2019): estimated heterogeneous effects often highly model dependent when using specification analogous to (1)
- Additional challenge: health is an intrinsically unobserved variable and a variety of proxies exist

We consider two data-driven alternatives for estimation of heterogeneous effects:

- Model-based recursive partitioning (Zeileis et al., 2008)
  - *Deterministic* model based clustering
- Latent class model with parameterized component probabilities
  - *Probabilistic* model based clustering

Model-based recursive partitioning

Recent research applies partitioning methods (e.g., regression trees) to the topic of heterogeneous causal effects (e.g., Athey and Imbens, 2015; Wager and Athey, 2018; Athey et al., 2019)

- Most previous literature has considered binary treatment effects under unconfoundedness

The model-based recursive partitioning procedure of Zeileis et al. (2008) is a suitable alternative for economic questions:

- Developed originally in computational statistics for linear and logistic regression
- Extended to psychometric models (Strobl et al., 2011, 2015) and to GLM and ML models (Rusch and Zeileis, 2013)
- We adapt the method to asymmetric outcome variables (using a Tobit model in each partition) with observed nuisance parameters

Algorithm 1: Tobit model-based recursive partitioning

1 **repeat**

2 Step 1: Fit the local Tobit model to the (sub-)dataset

- A side product of this step is each observation's contribution to the score function $\psi_{it} = \frac{\partial \Psi(y_{it}, X_{it}, \theta)}{\partial \theta}$

Step 2: Test for parameter instability along the observed features (using Zeileis and Hornik (2007)) and select feature with lowest *p*-value

Step 3: Perform exhaustive search over possible split points to find likelihood-maximizing threshold

Step 4: Split into sub-datasets

3 **until** *no further parameter instability is found*;

- Implemented in R using `partykit` library of Hothorn and Zeileis (2015)
- Non-adjusted standard errors (Zeileis et al., 2008)

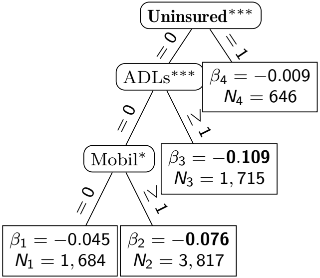
Results: Model-based recursive partitioning

- Allows the health proxies to be highly interactive
- Interpretation challenging due to wealth of estimation results
- Intuitive visualization through trees.

For each tree:

- Feature with most significant rejection of parameter stability is in top-node
- Edges emanating from node show the partition
- Within each leaf is
  (1) the estimated coefficient (> **95% sign.**)
  (2) the number of observations in corresponding partition

Figure 2: Results (Couple Households)



(a) log(total spending)

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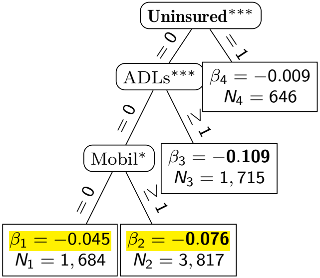

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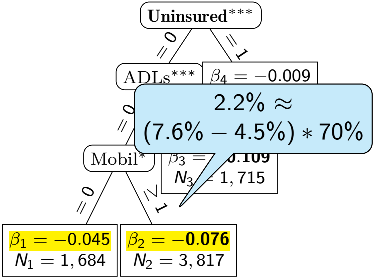

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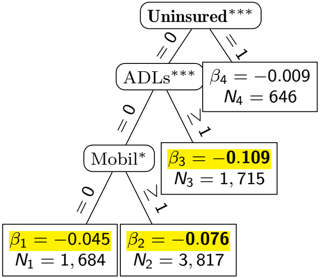

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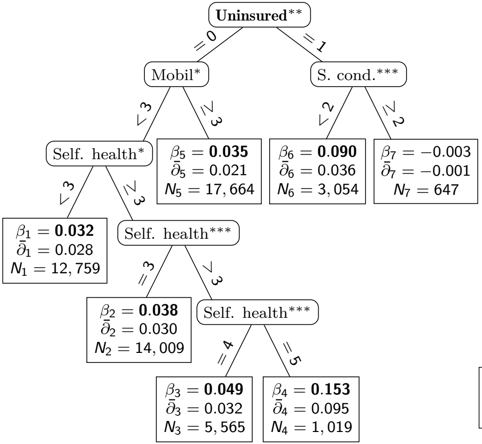
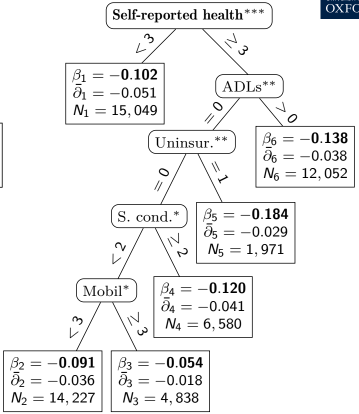


(b) Safe asset share



(c) Risky asset share

Results: Model-based recursive partitioning (2/2)

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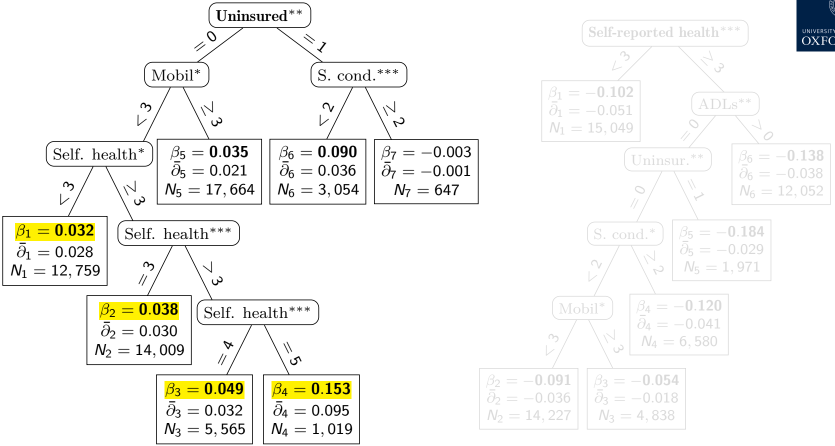

(b) Safe asset share

(c) Risky asset share

- Effect of health care policy uncertainty increasing with worse self-reported health in (b)

Results: Model-based recursive partitioning (2/2)

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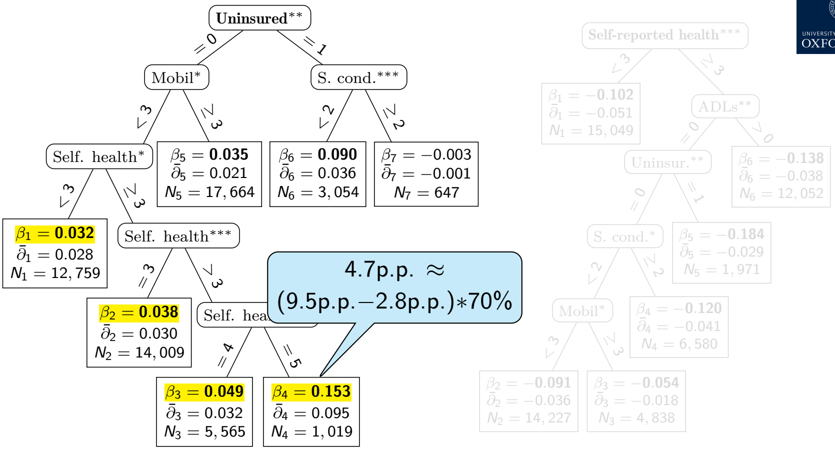

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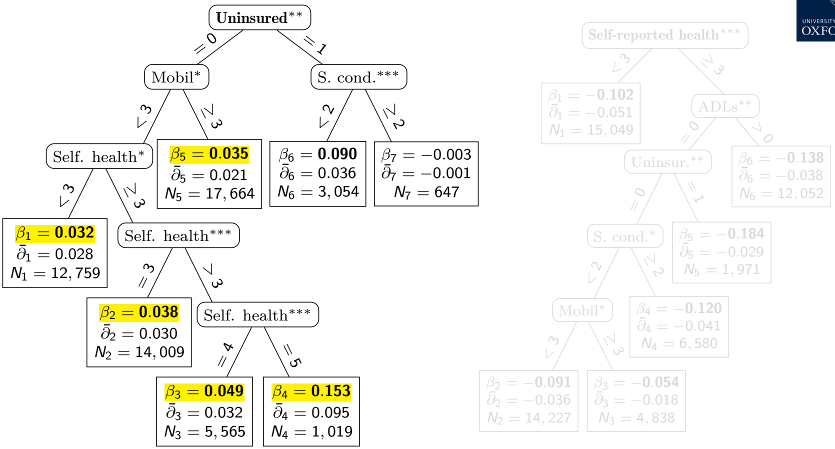

(b) Safe asset share

(c) Risky asset share

- Interpretation not always clear

Results: Model-based recursive partitioning (2/2)

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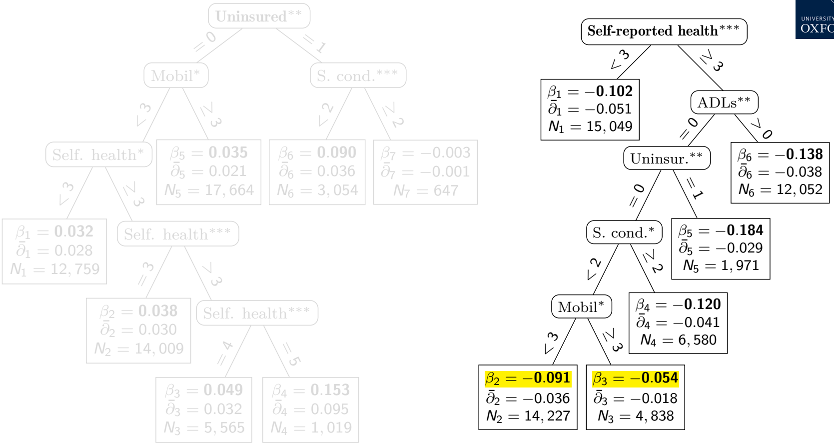

(b) Safe asset share

(c) Risky asset share

- Effect of health not strictly monotonic

Results: Model-based recursive partitioning (2/2)

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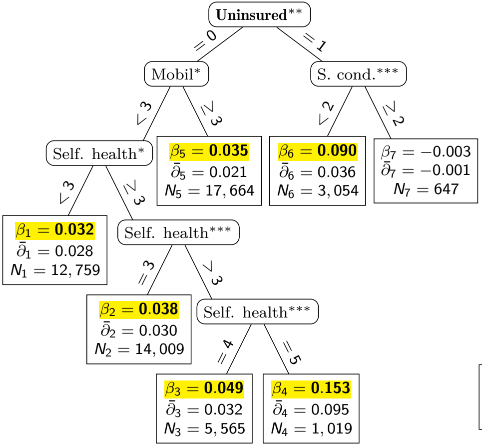

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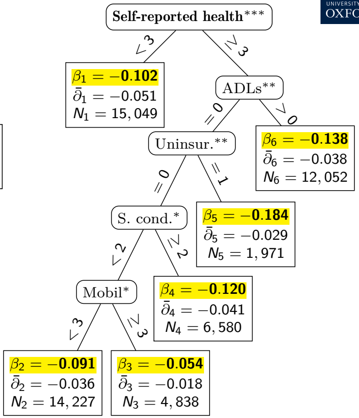

(c) Risky asset share

- Almost all partitions show significant effect with expected sign

Model-based recursive partitioning vs latent class model

Model-based recursive partitioning can be written as

$$y_{it} = \begin{cases} f(y_{it}|X_{it}, \theta_1), & \text{if } \{Z_{it}\} \in \mathcal{Z}_1 \\ \quad\vdots & \\ f(y_{it}|X_{it}, \theta_G), & \text{if } \{Z_{it}\} \in \mathcal{Z}_G \end{cases} \tag{2}$$

where a particular observation stems from the gth partition, $g = 1, \ldots, G$, if its features, $\{Z_{it}\}$, are elements of the partition's feature-space, $\mathcal{Z}_g$.

Latent class model can be written as

$$y_{it} = \begin{cases} f(y_{it}|X_{it}, \theta_1), & \text{if } S_{it} = 1 \\ \vdots & \\ f(y_{it}|X_{it}, \theta_M), & \text{if } S_{it} = M \end{cases} \tag{3}$$

where a particular observation stems from the mth component, $m = 1, \ldots, M$, if $S_{it} = m$. Here, S_{it} are realizations of the discrete random variable $\tilde{S}$ with corresponding probabilities $P[\tilde{S}_{it} = s] = \pi_{s,it}$ that satisfy $\sum_{s=1}^{M} \pi_{s,it} = 1$.

Methodology: Latent class model

Latent class models (LCMs) in health economics literature:

- LCMs used for analyzing heterogeneous health care utilization (e.g., Deb and Trivedi, 1997; Jiménez-Martín et al., 2002; Atella et al., 2004; Bago d'Uva, 2006)
- Component-probabilities $\pi_{s,it}$ can be parameterized (e.g., Bago d'Uva and Jones, 2009)
- We define

$$\pi_{s,it} = P[S_{it} = s | Z_{it}] = \frac{\exp\left(\alpha_{s,0} + Z_{it}\alpha_{s,1}\right)}{\sum_{j=1}^{M} \exp\left(\alpha_{j,0} + Z_{it}\alpha_{j,1}\right)}, \tag{4}$$

Computational caveat: number of components (M) needs to be fixed *a priori*.

- We consider $M = 2$
- Using α-coefficients in component probabilities π to infer whether natural labeling of components with respect to health is possible

Estimated in R using the EM Algorithm (Dempster et al., 1977); standard errors computed using nonparametric bootstrap

Results: Latent class model

Table 3: Prior Component Probabilities (Couples)

	(1) log(Total spending)		(2) Risky asset share		(3) Safe asset share	
Prior Probability						
Constant	0	-2.329	0	2.026***	0	-0.361***
Self-reported health	0	0.128	0	0.195***	0	0.293***
Severe conditions	0	0.067	0	-0.006	0	0.049***
Mobility	0	0.081	0	-0.008	0	0.066***
ADLs	0	0.166	0	0.004	0	0.028**
Nights in hospital	0	-0.003	0	-0.002	0	-0.001
Uninsured	0	1.336*	0	0.625***	0	0.838***
Components	*s.1*	*s.2*	*s.1*	*s.2*	*s.1*	*s.2*
Component share	0.804	0.196	0.067	0.933	0.318	0.682

Notes. *, ** and *** denote significance at 10%, 5%, 1% , respectively.

- No obvious natural labels associated with health for total spending
- Positive association between "worse" health and membership in component $s.2$ for risky and safe assets

Results: Latent class model

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Results: Latent class model (2/2)

Table 3: Component-specific effects (Couples)

	(1) log(Total spending)		(2) Risky asset share		(3) Safe asset share	
Components	*s.1*	*s.2*	*s.1*	*s.2*	*s.1*	*s.2*
$\log(\text{HPU}_{12})$	-0.088	-0.141	0.000	-0.103***	-0.002	0.076***
$\partial \log(\mathrm{HPU}_{12})\Big\rvert_{\bar{x}_C}$	-0.088	-0.141	0.000	-0.029	-0.002	0.037
Component share	0.804	0.196	0.067	0.933	0.318	0.682
Log-likelihood	-6,203.5		-29,669.4		-24,643.6	
Observations	7,862		54,717		54,717	

Notes. *, ** and *** denote significance at 10%, 5%, 1% , respectively.

- Components associated with "worse" health show significant and larger effect of health care policy uncertainty

Results: Latent class model (2/2)

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Conclusion

This study

- examines the effect of health care policy uncertainty on households' spending and portfolio choice
- develops a simple theoretical model to motivate negative effects on consumption and relative demand for risky assets
- performs an empirical analysis using a variety of econometric models, HRS/CAMS, and index of Baker et al. (2016)
- finds mixed evidence on total spending but a strong effect on portfolio choice
  - bad health magnifies effects

Estimates suggest that an uncertainty increase similar to that observed during the ACA repeal efforts decreases the relative demand for risky assets by as much as a considerable reduction in health (i.e., comparable to the estimates of Rosen and Wu (2004)).

- Health care policy uncertainty is a potentially important determinant of households' financial behavior

Thank you!

- Questions?
- Comments?
- Suggestions?
- Criticisms?

The following slides are to be omitted from the final presentation

Proposition 1:
Households decrease spending and relative investment in risky assets when faced with uncertainty about future costs of health care.

Table 2: Fixed Effect and Pooled Tobit Model Results

Couple households	Fixed effects log(Total spending)	Fixed effects Risky asset share	Pooled Risky asset share	Fixed effects Safe asset share	Pooled Safe asset share
$\log(\mathrm{HPU}_{12})$	-0.039***	-0.037***	-0.105***	0.022***	0.044***
$\bar{\partial}\log(\mathrm{HPU}_{12})$	-0.039		-0.040		0.031
Single households	Fixed effects log(Total spending)	Fixed effects Risky asset share	Pooled Risky asset share	Fixed effects Safe asset share	Pooled Safe asset share
$\log(\mathrm{HPU}_{12})$	-0.017	-0.052***	-0.146***	0.040***	0.061***
$\bar{\partial}\log(\mathrm{HPU}_{12})$	-0.017		-0.037		0.028

- Coefficients on controls are intuitive
  - Total spending, share in risky (safe) assets is monotonically increasing (decreasing) with income, wealth, education
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Proposition 1:
Households decrease spending and relative investment in risky assets when faced with uncertainty about future costs of health care.

Table 2: Fixed Effect and Pooled Tobit Model Results

Couple households	Fixed effects log(Total spending)	Fixed effects Risky asset share	Pooled Risky asset share	Fixed effects Safe asset share	Pooled Safe asset share
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References

Aaberge, R., Liu, K., and Zhu, Y. (2017). Political uncertainty and household savings. *Journal of Comparative Economics*, 45(1):154–1
Agarwal, V., Aslan, H., Huang, L., and Ren, H. (2018). Policy uncertainty and household stock market participation. Unpublished working paper, available at SSRN: `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3068792`.
Atella, V., Brindisi, F., Deb, P., and Rosati, F. C. (2004). Determinants of access to physician services in Italy: A latent class seemingly unrelated probit approach. *Health Economics*, 13(7):657–668.
Athey, S. and Imbens, G. W. (2015). Machine learning methods for estimating heterogeneous causal effects. Unpublished working paper, arXiv:1504.01132v1.
Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.
Bago d'Uva, T. (2006). Latent class models for utilisation of health care. *Health Economics*, 15(4):329–343.
Bago d'Uva, T. and Jones, A. M. (2009). Health care utilisation in Europe: New evidence from the ECHP. *Journal of Health Economics*, 28(2):265–279.
Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.
Berkowitz, M. K. and Qiu, J. (2006). A further look at household portfolio choice and health status. *Journal of Banking & Finance*, 30(4):1201–1217.
Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–76.
Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly Journal of Economics*, 112(1):1–55.
Deb, P. and Trivedi, P. K. (1997). Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics*, 12(3):313–336.
Delavande, A. and Rohwedder, S. (2011). Individuals' uncertainty about future social security benefits and portfolio choice. *Journal of Applied Econometrics*, 26(3):498–519.
Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38.
Edwards, R. D. (2008). Health risk and portfolio choice. *Journal of Business & Economic Statistics*, 26(4):472–485.
Fan, E. and Zhao, R. (2009). Health status and portfolio choice: Causality or heterogeneity? *Journal of Banking & Finance*, 33(6):1079–1088.
Gábor-Tóth, E. and Georgarakos, D. (2018). Economic policy uncertainty and stock market participation. Center for Financial Studies Working Paper No 590.
Giavazzi, F. and McMahon, M. (2012). Policy uncertainty and household savings. *Review of Economics and Statistics*, 94(2):517–531.
Goldman, D. and Maestas, N. (2013). Medical expenditure risk and household portfolio choice. *Journal of Applied Econometrics*, 28(4):527–550.
Gollier, C. and 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. and Yelowitz, A. (1999). Public health insurance and private savings. *Journal of Political Economy*, 107(6):1249–1274.
Gulen, H. and Ion, M. (2015). Policy uncertainty and corporate investment. *The Review of Financial Studies*, 29(3):523–564.
Hainmueller, J., Mummolo, J., and Xu, Y. (2019). How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice. *Political Analysis*, 27(2):163–192.
Honoré, B. E. (1992). Trimmed LAD and least squares estimation of truncated and censored regression models with fixed effects. *Econometrica*, 60(3):533–565.
Hothorn, T. and Zeileis, A. (2015). `partykit`: A modular toolkit for recursive partytioning in R. *The Journal of Machine Learning Research*, 16(1):3905–3909.