Knowledge of Future Job Loss and Implications for Unemployment Insurance

Nathaniel Hendren

Harvard and NBER

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Why is there not a robust private market for unemployment/job loss insurance?

- Like health, life, disability, car, home, pet health, iPhone water damage, etc...
- Why doesn’t Aetna sell UI?
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  - Why doesn’t Aetna sell UI?

Large literature studying “optimal” government provision of UI

Absence of private market not micro-founded
  - If a private market doesn’t exist, doesn’t that mean no one’s willing to pay for UI?
  - Does providing a microfoundation change how we should think about optimal benefits?
Overview of the Paper

- Private information is the reason the private market doesn’t exist
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  - Estimate cost of adverse selection if contracts were offered
    - Use information contained in subjective probability elicitation as noisy and biased measures of beliefs (Hendren 2013)
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  - Suggests existing approaches under-estimate UI demand
  - Provide “2-sample IV” corrections to account for realized information
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    - Provide “2-sample IV” corrections to account for realized information
- Willingness to pay below cost of adverse selection
- Characterize optimal UI
  - Previous approaches miss the ex-ante value of social insurance
    - Insurance against learning you might lose your job
    - Exploit ex-ante responses to measure this value
Outline

1. Model and No Trade Condition
2. Quantification of Private Information
3. Estimates of Willingness to Pay
4. Optimal UI and Ex-Ante WTP
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2. Quantification of Private Information

3. Estimates of Willingness to Pay

4. Optimal UI and Ex-Ante WTP
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- Individual faces risk of becoming unemployed
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  - Later: What if govt UI changed?
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- Individuals indexed by unobservable $\theta$ choose:
  - Probability $p$ of being unemployed, $p$
  - Consumption when employed, $c_e$, and unemployed, $c_u$ (incl $b$, $\tau$)
  - Other actions, $a$
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  - Consumption when employed, $c_e$, and unemployed, $c_u$ (incl $b$, $\tau$)
  - Other actions, $a$
  - Maximize:

$$\max_{p, c_e, c_u, a \in \Omega(\theta)} \left\{ (1 - p) \nu(c_e) + pu(c_u) + \Psi(p, a; \theta) \right\}$$
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    $$
- When can private markets profitably provide positive benefits, $b$, financed by premiums, $\tau$?
No Trade Condition

- Define $P$ to be a random variable of choices of $p$ with no additional private insurance: $b = \tau = 0$. 

\[ T(p) = \mathbb{E}\left[ P | P = p \right] \]

Is the “pooled price ratio” in Hendren (2013).

Generalizes no trade condition in Hendren (2013) to allow for moral hazard.

Market existence is independent of moral hazard problem (Shavell, 1979).
No Trade Condition

- Define $P$ to be a random variable of choices of $p$ with no additional private insurance: $b = \tau = 0$.

- Simplification: the choice of $p$ summarizes the heterogeneity in types (i.e. $\theta \rightarrow p$ is 1-1).
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No profitable trade is feasible whenever

$$\frac{u'(c_u(p))}{\nu'(c_e(p))} \leq T(p) \quad \forall p$$

where

$$T(p) = \frac{E[P|P \geq p]}{E[1-P|P \geq p]} \frac{1-p}{p}$$

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Two measures of $T(p)$:
Estimand: Minimum Pooled Price Ratio

- Two measures of $T(p)$:
  - Minimum pooled price ratio, $\inf_p T(p)$
    - Relevant if insurers know $T(p)$

Average pooled price ratio provides measure of frictions imposed on insurance company that needs to experiment to open up the market. Will estimate lower bounds for $\mathbb{E}[T(p)]$ using fewer assumptions than $\inf_p T(p)$. 

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Will estimate lower bounds for $E[T(P)]$ using fewer assumptions than $\inf T(p)$
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2. Quantification of Private Information

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- Standard approach uses revealed preference (Chiappori and Salanie, 2000; Finkelstein and Poterba, 2002; Einav et. al., 2010)
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Use data from Health and Retirement Study (1993-2013)

- Survey asks subjective probability elicitations, $Z$
  - “What is percent chance (0-100) that you will lose your job in the next 12 months?”
Elicitations as Noisy Measures of Beliefs

- $Z$ may not express an agents’ true beliefs ($Z \neq P$)
Elicitations as Noisy Measures of Beliefs

- $Z$ may not express an agents’ true beliefs ($Z \neq P$)
- Use information in joint distribution of elicitation and event

Define $U$ as indicator for involuntary job loss in next 12 months

Does $Z$ predict $U$ conditional on $X$?

Sets of controls simulate different underwriting strategies

Start with controls for demographics + job characteristics

Demographics (gender, age quadratic, census division, year)

Job characteristics (tenure quadratic, occupation dummies, industry dummies, log wage quadratic)

Add additional controls for health, unemployment history, etc.

Bin $Z$ into groups, $c_j$, (0, 1-10, ...)

Regress $U$ on $X$ and bins to construct:

$$P(Z) = \Pr\{U | X, Z\} = b_X + \hat{\beta}_j z_j 1\{Z \in c_j\}$$
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- Bin $Z$ into groups, $\chi_j$, (0, 1-10, ...)
  - Regress $U$ on $X$ and bins to construct:
    $$P_Z = \Pr \{ U|X, Z \} = \beta X + \sum_j \zeta_j 1 \{ Z \in \chi_j \}$$
Predictive Content of Elicitations about Future Unemployment

Coefficients on Z categories in Pr\{U|Z,X\}

Subjective Probability Elicitation (Z)
Let $P_Z = \Pr \{U|Z, X\}$

- $P_Z$ is related to distribution of true beliefs, $P$
Let $P_Z = \Pr \{ U \mid Z, X \}$

- $P_Z$ is related to distribution of true beliefs, $P$

Two assumptions:

1. Elicitations not more informative than true beliefs
   
   $\Pr \{ U \mid Z, X, P \} = \Pr \{ U \mid X, P \}$

2. True beliefs (not elicitations) are unbiased
   
   $\Pr \{ U \mid X, P \} = P$
Relate to True Beliefs

- Let \( P_Z = \Pr \{ U \mid Z, X \} \)
- \( P_Z \) is related to distribution of true beliefs, \( P \)

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- Assumptions 1+2 imply:
  $$P_Z = E[P|X, Z]$$
Predictive Content of Elicitations about Future Unemployment

Distribution of $\Pr\{U|Z,X\} - \Pr\{U|X\}$
Can use distribution of predicted values to provide non-parametric lower bound on $E[T(p)]$
Lower Bound on $E[T(p)]$

- Can use distribution of predicted values to provide non-parametric lower bound on $E[T(P)]$
- Define

$$T_Z(p) = 1 + \frac{E[P_Z - p | P_Z \geq p]}{Pr\{U\}}$$
Lower Bound on $E[T(p)]$

- Can use distribution of predicted values to provide non-parametric lower bound on $E[T(P)]$
- Define
  \[
  T_Z(p) = 1 + E[P_Z - p | P_Z \geq p] / Pr\{U\}
  \]
- **Proposition 1:** Assumptions 1 and 2 imply:
  \[
  E[T_Z(P_Z)] \leq E[T(P)]
  \]
Lower Bounds for $E[T(P)]^{-1}$ using Alternative Controls
Lower Bounds for $E[T(P)]-1$ by Industry
Lower Bounds for $E[T(P)] - 1$ by Occupation
Lower Bounds for E[T(P)]-1 by Age
Lower Bounds on $E[T(P)] - 1$ using Alternative $U$ Definitions
Lower Bounds for $E[T(P)] - 1$ for Low Risk Sub-samples

- 5+ Years Job Tenure
- Working Last Wave
  - No UI claim in past 4 years
- Not Working Last Wave
Estimation of inf $T(p)$

- Add parametric assumption to $f_{Z|P}(Z|P) = f_{Z|P}(Z|P; \eta)$ to reduce dimensionality
Estimation of \( T(p) \)

- Add parametric assumption to \( f_{Z|P}(Z|P) = f_{Z|P}(Z|P; \eta) \) to reduce dimensionality
  - Approach discussed in detail in Hendren (2013)
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- Add parametric assumption to $f_{Z|P}(Z|P) = f_{Z|P}(Z|P; \eta)$ to reduce dimensionality
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  - Expand observed density (cond’l on $X = x$)

\[
 f_{Z,U}(Z, U) = \int f_{Z,U}(Z, U|p) f_P(p) \, dp \\
= \int \Pr\{U = 1|Z, P = p\} U (1 - \Pr\{U = 1|Z, P = p\} \\
* f_{Z|P}(Z|P = p; \eta) f_P(p) \, dp \\
= \int p^U (1 - p)^{1-U} \underbrace{f_{Z|P}(Z|P; \eta)}_{\text{Parametric}} \underbrace{f_P(p)}_{\text{Flexible}} \, dp
\]
Estimation of inf $T(p)$

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$$f_{Z,U}(Z,U) = \int f_{Z,U}(Z,U|p) f_P(p) \, dp$$

$$= \int \Pr\{U = 1|Z, P = p\} U (1 - \Pr\{U = 1|Z, P = p\} \times f_{Z|P}(Z|P = p; \eta) f_P(p) \, dp$$

$$= \int p^U (1 - p)^{1-U} \left( \underbrace{f_{Z|P}(Z|P; \eta)}_{\text{Parametric}} \right) \left( \underbrace{f_P(p)}_{\text{Flexible}} \right) \, dp$$

- Approximate $f_P(p)$ using point-mass and $f_{Z|P}$ using normal + ordered probit (as in Hendren 2013)
- Construct $T(p)$ and its minimum (excluding top point mass)
## Minimum Pooled Price Ratio

<table>
<thead>
<tr>
<th>Specification</th>
<th>Baseline (1)</th>
<th>Alternative Controls (2)</th>
<th>Alternative Controls (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inf T(p) - 1</td>
<td>3.360</td>
<td>5.301</td>
<td>3.228</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.203)</td>
<td>(0.655)</td>
<td>(0.268)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographics</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Job Characteristics</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Health Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>26,640</td>
<td>26,640</td>
<td>22,831</td>
</tr>
<tr>
<td>Num of HHs</td>
<td>3,467</td>
<td>3,467</td>
<td>3,180</td>
</tr>
</tbody>
</table>
## Minimum Pooled Price Ratio

<table>
<thead>
<tr>
<th>Specification</th>
<th>Sub-Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age &lt;= 55</td>
</tr>
<tr>
<td>Inf T(p) - 1</td>
<td>3.325</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.306)</td>
</tr>
</tbody>
</table>

### Controls
- Demographics: X X X X X X X X
- Job Characteristics: X X X X X X X X

| Num of Obs.    | 11,134 | 15,506   | 13,320           | 13,320           | 17,850       | 8,790        |
| Num of HHs     | 2,255  | 3,231    | 2,916            | 2,259            | 2,952        | 2,437        |
Comparison of inf $T(p)$ to Other Markets
Life, Disability, and LTC Estimates from Hendren (2013)
Comparison of \( \inf T(p) \) to Other Markets
Life, Disability, and LTC Estimates from Hendren (2013)

Markets Exclude “Pre-existing Conditions”

No Market Exists
Market Exists
1. Model and No Trade Condition

2. Quantification of Private Information

3. Estimates of Willingness to Pay

4. Optimal UI and Ex-Ante WTP
Willingness to Pay

How much of a markup are individuals willing to pay, \( \frac{u'(c_u(p))}{v'(c_e(p))} \)?

Follow previous literature (Baily 1978, Chetty 2006, ...)

\[ u_0(u(c_u(p))) v_0(c_e(p)) \]

\[ \gamma + s\Delta c(c(p)) \]

\[ s = u_00c_u0u_0c_e0 \]

is the coefficient of relative risk aversion

Assumes no state dependence:

\[ u = v \]

“\( \gamma \) denotes:

\[ 2nd \ order \ Taylor \ approximation \ (u_000\gamma_0) \]

\[ \log(1+x) \approx x \]

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Willingness to Pay

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- Follow previous literature (Baily 1978, Chetty 2006,...) by assuming:

\[
\frac{u'(c_u(p))}{v'(c_e(p))} \approx 1 + \sigma \frac{\Delta c}{c}(p)
\]

where

\[
\frac{\Delta c}{c}(p) = \frac{c_e(p) - c_u(p)}{c_e(p)} \approx \log(c_e(p)) - \log(c_u(p))
\]

\(Dc\)

\(u_0\)

\(v_0\)

\(\sigma\)

\(\Delta c\)

\(c\)

\(\log\)

\(c_e\)

\(c_u\)
Willingness to Pay

- How much of a markup are individuals willing to pay, \( \frac{u'(c_u(p))}{v'(c_e(p))} \)?
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\]

where

\[
\frac{\Delta c}{c}(p) = \frac{c_e(p) - c_u(p)}{c_e(p)} \approx \log(c_e(p)) - \log(c_u(p))
\]

- \( \sigma = \frac{u''c}{u'} \) is the coeff of relative risk aversion
- Assumes no state dependence: \( u = v \)
- \( \approx \) denotes:
  - 2nd order Taylor approximation (\( u''' \approx 0 \))
  - \( \log(1 + x) \approx x \)
First Differences in Consumption

- Start by estimating the average causal effect: $E \left[ \frac{\Delta c}{c} \right]$
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First Differences in Consumption

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- Regression of \( c \) on \( U \) would be biased
- Common to use 1-year first differences:

\[
\Delta^{FD} = E \left[ \log(c_t) - \log(c_{t-1}) \mid U_t = 1 \right] - E \left[ \log(c_t) - \log(c_{t-1}) \mid U_t = 0 \right]
\]
First Differences in Consumption

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\]

- Use food expenditure in PSID
  - Following Gruber (1997) and Chetty and Szeidl (2007)
  - Previous literature finds \( \Delta^{FD} \approx 6 - 10\% \)
## Food Expenditure Drop Upon Unemployment

<table>
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<tr>
<th>Specification:</th>
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<tbody>
<tr>
<td>Impact on log($c_{t-1}$)-log($c_t$)</td>
<td>Employed</td>
</tr>
<tr>
<td>Unemp</td>
<td>-0.0753***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00857)</td>
</tr>
</tbody>
</table>

### Specification Details

- Sample Employed in t-1: X X X
- Controls for change in log needs: X X
Identification concerns

- If individuals learn about unemployment, lagged consumption may respond to future unemployment

\[ \Delta^{FD} = E[\log(c_e) - \log(c_u)] - (E[\log(c_{pre})|U=0] - E[\log(c_{pre})|U=1]) \]

  Causal Effect  
  
  Bias from ex-ante response

- Can be biased from correlated income shocks or savings responses
Identification concerns

If individuals learn about unemployment, lagged consumption may respond to future unemployment

\[
\Delta^{FD} = \left( E \left[ \log(c_e) - \log(c_u) \right] - (E \left[ \log(c_{pre}) \mid U = 0 \right] - E \left[ \log(c_{pre}) \mid U = 1 \right]) \right) - \left( E \left[ \log(c_{pre}) \mid U = 0 \right] - E \left[ \log(c_{pre}) \mid U = 1 \right] \right)
\]

Causal Effect

Bias from ex-ante response

Can be biased from correlated income shocks or savings responses

Event study using leads/lags:

- Regress \( g_t = \log(c_t) - \log(c_{t-1}) \) on \( U_{t+j} \)
- Control for age cubic and year dummies
Impact of Unemployment on Consumption Growth

Employed in t-2 and t-1 Sample

Coefficient on Unemployment Indicator

Lead/Lag Relative to Unemployment Measurement

Coeff 5%/95% CI

Impact of Unemployment on Consumption Growth
## Impact of Future Job Loss on Consumption

**Specification:**

<table>
<thead>
<tr>
<th>Impact of Unemployment on log($c_{t-2}$)-log($c_{t-1}$)</th>
<th>Controls for</th>
<th>Employed</th>
<th>Needs</th>
<th>Job Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemp</td>
<td></td>
<td>-0.0230**</td>
<td>-0.0232**</td>
<td>-0.0182**</td>
</tr>
<tr>
<td>s.e.</td>
<td></td>
<td>(0.00954)</td>
<td>(0.0101)</td>
<td>(0.00854)</td>
</tr>
</tbody>
</table>

**Specification Details**

- Sample Employed in t-2 and t-1: X X X
- Controls for change in log needs (t-2 vs t-1): X X
IV Solution: Scale by Information Revealed

- How to recover causal effect from $\Delta^{FD}$?
IV Solution: Scale by Information Revealed

- How to recover causal effect from $\Delta^{FD}$?
- Two assumptions:
How to recover causal effect from $\Delta^{FD}$?

Two assumptions:

1. Euler equation holds

$$v'\left(c_{pre}(p)\right) = pu'\left(c_{u}(p)\right) + (1-p) v'\left(c_{e}(p)\right)$$
How to recover causal effect from $\Delta^{FD}$?

Two assumptions:

1. Euler equation holds

$$v'(c_{pre}(p)) = pu'(c_u(p)) + (1 - p)v'(c_e(p))$$

2. Causal effect doesn’t vary with $p$: $\frac{d[\log(c_e) - \log(c_u)]}{dp} = 0$ (allows heterogeneity in $\frac{d\log(c_e)}{dp}$)
How to recover causal effect from $\Delta^{FD}$?

Two assumptions:

1. Euler equation holds

\[ \nu' (c_{pre}(p)) = pu' (c_u(p)) + (1 - p) \nu' (c_e(p)) \]

2. Causal effect doesn’t vary with $p$:

\[ \frac{d[\log(c_e) - \log(c_u)]}{dp} = 0 \] (allows heterogeneity in $\frac{d\log(c_e)}{dp}$)

Proposition: Suppose (1) and (2) hold. Then,

\[ E[\log(c_e(p)) - \log(c_u(p))] = \frac{\Delta^{FD}}{1 - (E[P|U = 1] - E[P|U = 0])} \]
How to recover causal effect from $\Delta^{FD}$?

Two assumptions:

1. Euler equation holds
   \[
   v' (c_{pre} (p)) = pu' (c_u (p)) + (1 - p) v' (c_e (p))
   \]

2. Causal effect doesn’t vary with $p$: \( \frac{d[\log(c_e) - \log(c_u)]}{dp} = 0 \) (allows heterogeneity in \( \frac{d\log(c_e)}{dp} \))

Proposition: Suppose (1) and (2) hold. Then,

\[
E [\log (c_e (p)) - \log (c_u (p))] = \frac{\Delta^{FD}}{1 - (E [P|U = 1] - E [P|U = 0])}
\]

Scale by information revealed between \( t - 1 \) and \( t \)

\[
\frac{\text{var} (P)}{\text{var} (U)} = E [P|U = 1] - E [P|U = 0]
\]
First Stage

- Don’t observe beliefs in PSID
  - Use HRS to obtain $E[P|U = 1] - E[P|U = 0]$
First Stage

- Don’t observe beliefs in PSID
  - Use HRS to obtain $E[P|U = 1] - E[P|U = 0]$
  - Regress $Z$ on $U$:

$$E[P|U = 1] - E[P|U = 0] \approx E[Z|U = 1] - E[Z|U = 0]$$

- Recovers first stage under classical measurement error (noisy and biased $Z$)
- Biased if measurement error is correlated with $U$
First Stage

Don’t observe beliefs in PSID

- Use HRS to obtain $E[P|U = 1] - E[P|U = 0]$
- Regress $Z$ on $U$:

$$E[P|U = 1] - E[P|U = 0] \approx E[Z|U = 1] - E[Z|U = 0]$$

- Recovers first stage under classical measurement error (noisy and biased $Z$)
- Biased if measurement error is correlated with $U$
- Yields $E[Z|U = 1] - E[Z|U = 0] \approx 0.20$
- Implies $1 - (E[P|U = 1] - E[P|U = 0]) \approx 0.8$
## Impact of Job Loss on Consumption

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Employed</th>
<th>Controls for Needs</th>
<th>Job Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impact on log(c_{t-1})-log(c_t)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>-0.0753***</td>
<td>-0.0720***</td>
<td>-0.0509***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00857)</td>
<td>(0.00891)</td>
<td>(0.00772)</td>
</tr>
<tr>
<td>First Stage Impact on P</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0123)</td>
<td>(0.0123)</td>
<td>(0.0123)</td>
</tr>
<tr>
<td>IV Impact of U on log(c_t)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.094***</td>
<td>-0.09***</td>
<td>-0.063***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0107)</td>
<td>(0.0111)</td>
<td>(0.0096)</td>
</tr>
<tr>
<td>Markup WTP for UI (σ = 2)</td>
<td>18.7%</td>
<td>17.9%</td>
<td>12.7%</td>
</tr>
</tbody>
</table>
Range of specifications / robustness tests yield WTP between 15-50%
Range of specifications / robustness tests yield WTP between 15-50%

Private information provides micro-foundation for absence of market:

\[
\frac{u'}{v'} - 1 \leq \inf T(p) - 1 \\
[15\%, 50\%] \leq 300\%
\]
Range of specifications / robustness tests yield WTP between 15-50%

Private information provides micro-foundation for absence of market:

\[
\frac{u'}{v'} - 1 \leq \inf T(p) - 1
\]

\[\text{[15\%, 50\%]} \leq 300\%
\]

What if government decreased UI benefits?

- Gruber (1997): Consumption drop would increase 2-3x
- Suggests private market would likely not arise even if government stopped providing UI
Range of specifications / robustness tests yield WTP between 15-50%

Private information provides micro-foundation for absence of market:

\[
\frac{u'}{v'} - 1 \leq \inf T(p) - 1
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\[
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\]

What if government decreased UI benefits?

- Gruber (1997): Consumption drop would increase 2-3x
- Suggests private market would likely not arise even if government stopped providing UI

Does this change the calculus for optimal UI policy?
1. Model and No Trade Condition

2. Quantification of Private Information

3. Estimates of Willingness to Pay

4. Optimal UI and Ex-Ante WTP
Optimality Condition for UI

Return to theoretical model; solve for optimal $b$ and $\tau$
Optimality Condition for UI

- Return to theoretical model; solve for optimal $b$ and $\tau$
- Optimality formula:

$$W_{Social} = \frac{E \left[ \frac{p}{E[p]} u' (c_u (p)) \right] - E \left[ \frac{1-p}{E[1-p]} v' (c_e (p)) \right]}{E \left[ \frac{1-p}{E[1-p]} v' (c_e (p)) \right]} = FE$$

where $W_{Social}$ is the markup individuals are willing to pay before learning $p$

- $FE$ is the aggregate fiscal externality from increasing benefits
Return to theoretical model; solve for optimal $b$ and $\tau$

Optimality formula:

$$W^{Social} = E \left[ \frac{p}{E[p]} u' (c_u (p)) \right] - E \left[ \frac{1-p}{E[1-p]} v' (c_e (p)) \right] = FE$$

where $W^{Social}$ is the markup individuals are willing to pay before learning $p$

- $FE$ is the aggregate fiscal externality from increasing benefits
- Recovers Baily-Chetty formula if $p = E [p]$
- Causal effect of unemployment would be sufficient
Return to theoretical model; solve for optimal \( b \) and \( \tau \)

Optimality formula:

\[
W_{Social} = \frac{E \left[ \frac{p}{E[p]} u' (c_u (p)) \right] - E \left[ \frac{1-p}{E[1-p]} v' (c_e (p)) \right]}{E \left[ \frac{1-p}{E[1-p]} v' (c_e (p)) \right]} = FE
\]

where \( W_{Social} \) is the markup individuals are willing to pay before learning \( p \)

- \( FE \) is the aggregate fiscal externality from increasing benefits
- Recovers Baily-Chetty formula if \( p = E [p] \)
  - Causal effect of unemployment would be sufficient
- More generally, insurance moves resources across people with different ex-ante beliefs \( p \)
Consider welfare experiment:

\[ W^{\text{ex-ante}} = \frac{v'(c_{\text{pre}}(1)) - v'(c_{\text{pre}}(0))}{v'(c_{\text{pre}}(0))} \]

\[ \approx \frac{\frac{d}{dp}v'}{v'} \approx \frac{d\log(v')}{dp} \]
Consider welfare experiment:

\[ W_{\text{ex-ante}} = \frac{v'(c_{\text{pre}}(1)) - v'(c_{\text{pre}}(0))}{v'(c_{\text{pre}}(0))} \approx \frac{d}{dp} \frac{v'}{v'} \approx \frac{d \log(v')}{dp} \]

Suppose Assumptions 1 + 2 hold. Then:

\[ W_{\text{Social}} \approx \frac{\text{var}(P)}{\text{var}(U)} W_{\text{ex-ante}} + \left(1 - \frac{\text{var}(P)}{\text{var}(U)}\right) W_{\text{ex-post}} \]

\[ \sigma_{\Delta FD} \text{ (Gruber (1997))} \]

Social value of insurance includes ex-ante value
Paper provides two methods to estimate $W^{Ex-ante}$

\[ W^{Ex-ante} = \frac{d\log(v')}{dp} \approx \sigma \frac{d\log(c_{pre})}{dp} \approx \frac{1}{\varepsilon^{semi}} \frac{dLFP^{Spouse}}{dp} \]
2-Sample Estimation

- Paper provides two methods to estimate $W^{Ex-ante}$

$$W^{Ex-ante} = \frac{d\log (v')}{dp} \approx \sigma \frac{d\log (c_{pre})}{dp} \approx \frac{1}{\epsilon^{semi}} \frac{dLFP^{Spouse}}{dp}$$

- Estimate $\frac{d\log (c_{pre})}{dp}$ using 2-Sample IV:

$$\frac{d\log (c_{pre})}{dp} = \frac{\Delta^{FD}_{-1}}{\Delta^{P}_{-1}}$$

- Allows $\theta$ to move both $c$ and $p$ (e.g. income shocks)
2-Sample Estimation

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  - $\Delta^{FD}_{-1} \approx 2.5\%$ is the lagged first difference estimate
2-Sample Estimation

- Paper provides two methods to estimate $W^{Ex-ante}$

\[ W^{Ex-ante} = \frac{d \log (v')}{dp} \approx \sigma \frac{d \log (c_{pre})}{dp} \approx \frac{1}{\epsilon_{semi}} \frac{dLFP^{Spouse}}{dp} \]

- Estimate $\frac{d \log (c_{pre})}{dp}$ using 2-Sample IV:

\[ \frac{d \log (c_{pre})}{dp} = \frac{\Delta_{-1}^{FD}}{\Delta_{-1}^{P}} \]

- Allows $\theta$ to move both $c$ and $p$ (e.g. income shocks)

- $\Delta_{-1}^{FD} \approx 2.5\%$ is the lagged first difference estimate

- $\Delta_{-1}^{P}$ is lagged first difference in beliefs

\[ \Delta_{-1}^{P} = E[P | U_t = 1] - E[P | U_t = 0] - (E[P_{-1} | U_t = 1] - E[P_{-1} | U_t = 0]) \]

- Approximate $\Delta_{-1}^{P}$ by regressing $Z_t$ on $U_{t+j}$
## Impact of Future Job Loss on Consumption

<table>
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<tr>
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<tr>
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<td>-0.0232**</td>
<td>-0.0182**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00954)</td>
<td>(0.0101)</td>
<td>(0.00854)</td>
</tr>
<tr>
<td>2-Sample IV Welfare Calculation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coefficient on U (&quot;First Stage&quot;)</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Consumption Drop Equivalent</td>
<td>0.22***</td>
<td>0.23**</td>
<td>0.18**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.093)</td>
<td>(0.098)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Implied WTP (CRRA = 2)</td>
<td>0.45***</td>
<td>0.45**</td>
<td>0.35**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.185)</td>
<td>(0.195)</td>
<td>(0.166)</td>
</tr>
</tbody>
</table>
Summary of Ex-Ante WTP

- Paper also provides evidence based on ex-ante spousal labor supply responses

\[ W^{Ex-ante} = \frac{d\log(v')}{dp} \approx \frac{1}{e^{semi}} \frac{d[LFP^{Spouse}]}{dp} \]

- Suggests WTP of 50-60%
## Ex-ante Valuation Method:

<table>
<thead>
<tr>
<th>Social WTP, $W^{social}$</th>
<th>Consumption Drop</th>
<th>Labor Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td>23.8%</td>
<td>11.9%</td>
<td>35.7%</td>
</tr>
<tr>
<td>Only using $\Delta^{FD}$ (Gruber 1997)</td>
<td>15.1%</td>
<td>7.5%</td>
</tr>
<tr>
<td>% Not Captured</td>
<td>36.8%</td>
<td>36.8%</td>
</tr>
</tbody>
</table>

Insurance against $p$, $W^{ex-ante}$

| Weight, $E[P|U=1] - E[P|U=0]$ | 0.197            | 0.197        | 0.197        | 0.197        |

Insurance against $U$ (given $p$), $W^{ex-post}$

| Weight, $1 - (E[P|U=1] - E[P|U=0])$ | 0.803            | 0.803        | 0.803        | 0.803        |

### Specification Details

<table>
<thead>
<tr>
<th>CRRA, $\sigma$</th>
<th>2</th>
<th>1</th>
<th>3</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spouse L.S. Semi-Elasticity, $\varepsilon^{semi}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.5</td>
</tr>
</tbody>
</table>
Private information explains absence of private UI market
  - Growing evidence that private information shapes the existence of insurance markets

Knowledge of future job loss biases WTP estimates
  - Ex-ante consumption and spousal labor supply responses

Re-scale private WTP (25% higher)

Add ex-ante insurance value to social WTP (40% higher)
  - Larger than 25% because $W_{Ex-ante} > W_{Ex-post}$
    - UI partially insures against learning you might lose your job
Appendix
Further evidence of ex-ante responses?

- Spousal labor supply
  - If lower preferences for consumption, then spousal labor supply should decrease

Also provides new quantification of WTP

- Assume disutility of labor entry additively separable:

\[
W^{\text{Ex-ante}} = \frac{d\log (v')}{dp} \approx \frac{1}{\epsilon^{\text{semi}}} \frac{d[LFP^{\text{Spouse}}]}{dp}
\]
Observe elicitations and spousal labor supply jointly in HRS

Sample of households who stay married in $t - 1$ and $t$

Focus on labor market entry

Define an indicator for a spouse not in labor force last period and in labor force this period

- On average, about 4% of spouses go from not working to working
- Paper also looks at exit
  - Evidence of correlated shocks on exit
  - Suggests current approach may under-state response if opportunity set held fixed
Relationship between Potential Job Loss and Spousal Labor Supply
## Welfare Calculation: Spousal Labor Supply Response

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Baseline</th>
<th>U=0</th>
<th>HH FE</th>
<th>Ind FE</th>
<th>2yr Lag (&quot;Placebo&quot;)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Estimation of dL/dZ</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elicitation (Z)</td>
<td>0.0273**</td>
<td>0.0270**</td>
<td>0.0267*</td>
<td>0.0312</td>
<td>0.00792</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0112)</td>
<td>(0.0116)</td>
<td>(0.0146)</td>
<td>(0.0230)</td>
<td>(0.0102)</td>
</tr>
<tr>
<td><strong>Mean Dep Var</strong></td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>Num of Obs.</strong></td>
<td>11049</td>
<td>10726</td>
<td>11049</td>
<td>11049</td>
<td>11049</td>
</tr>
<tr>
<td><strong>Num of HHs</strong></td>
<td>2214</td>
<td>2194</td>
<td>2214</td>
<td>2214</td>
<td>2214</td>
</tr>
</tbody>
</table>
Assume $\epsilon_{semi} = 0.5$

Need to correct for measurement error in $Z$

$$\frac{dLFP}{dP} = \frac{dLFP}{dZ} \frac{\text{var}(Z)}{\text{var}(P)}$$

Again, use information in the joint distribution of $Z$ and $L$

$$\text{var}(P) \approx \text{cov}(L, Z)$$

So,

$$\frac{d\log(v')}{dp} \approx \frac{1}{\epsilon_{semi}} \frac{d[LFP^{Spouse}]}{dp} = \frac{1}{\epsilon_{semi}} \frac{dLFP}{dZ} \frac{\text{var}(Z)}{\text{var}(P)}$$
### Welfare Calculation: Spousal Labor Supply Response

<table>
<thead>
<tr>
<th>Specification:</th>
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<td>(0.0146)</td>
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<td>(0.0102)</td>
</tr>
<tr>
<td><strong>Welfare Calculation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total/Signal Var</td>
<td>11.00</td>
<td>11.00</td>
<td>11.00</td>
<td>11.00</td>
<td>11.00</td>
</tr>
<tr>
<td>bootstrap s.e.</td>
<td>(1.41)</td>
<td>(1.37)</td>
<td>(1.32)</td>
<td>(1.32)</td>
<td></td>
</tr>
<tr>
<td>Implied WTP (ε_{semi} = 0.5)</td>
<td>0.6**</td>
<td>0.59**</td>
<td>0.59**</td>
<td>0.69*</td>
<td></td>
</tr>
<tr>
<td>bootstrap s.e.</td>
<td>(0.26)</td>
<td>(0.26)</td>
<td>(0.29)</td>
<td>(0.39)</td>
<td></td>
</tr>
<tr>
<td>Mean Dep Var</td>
<td>0.04</td>
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<td>2194</td>
<td>2214</td>
<td>2214</td>
<td>2214</td>
</tr>
</tbody>
</table>
Assumptions

- Recovers causal effect under two assumptions:
  1. Euler equation holds
     \[ v' (c_{pre}(p)) = pu' (c_u(p)) + (1 - p) v' (c_e(p)) \]
  2. Heterogeneity in \( p \) may be correlated with \( c_u \) and \( c_e \), but not differentially
     \( \left( \frac{d \log(c_u)}{d p} \right) \approx \left( \frac{d \log(c_e)}{d p} \right) \)
Household Income Pattern around Unemployment

Employed in t-1 and t-2 sample

Coefficient on Unemployment Indicator

<table>
<thead>
<tr>
<th>Lead/Lag Relative to Unemployment Measurement</th>
<th>-4</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coeff</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5 / 95% CI
Ex-Post Consumption Impact

- Do $c_u$ and $c_e$ vary with $p$?
- Use consumption mail survey in HRS conducted in year after main survey
  - 10%(!) sub-sample
  - Regress ex-post consumption $\log(c)$ on ex-ante $Z$
    - Recall: $Z$ has large focal point bias at zero
  - Controls for wages, census division, year, age, gender, marital status, and unemployment status
Relationship between Potential Job Loss and Consumption

Household Consumption per Capita
Relationship between Potential Job Loss and Consumption
Leads and Lags of Per Capita Consumption

Years Relative to Elicitation Measurement

Coeff on Subj. Prob. Elic.
## Sample Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Panel 1: Baseline Sample</th>
<th>Panel 2: Health Sample</th>
<th>Panel 3: Married Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std dev</td>
<td>mean</td>
</tr>
<tr>
<td><strong>Selected Observables (subset of X)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>56.1</td>
<td>5.1</td>
<td>56.1</td>
</tr>
<tr>
<td>Male</td>
<td>0.40</td>
<td>0.49</td>
<td>0.41</td>
</tr>
<tr>
<td>Wage</td>
<td>36,057</td>
<td>143,883</td>
<td>37,523</td>
</tr>
<tr>
<td>Job Tenure (Years)</td>
<td>12.7</td>
<td>10.8</td>
<td>12.7</td>
</tr>
<tr>
<td><strong>Unemployment Outcome (U)</strong></td>
<td>0.031</td>
<td>0.173</td>
<td>0.032</td>
</tr>
<tr>
<td><strong>Subjective Probability Elicitatio</strong></td>
<td>15.7</td>
<td>24.8</td>
<td>15.7</td>
</tr>
<tr>
<td><strong>Spousal Labor Supply</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working for Pay</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction Entering</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sample Size</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>26,640</td>
<td></td>
<td>22,831</td>
</tr>
<tr>
<td>Number of Households</td>
<td>3,467</td>
<td></td>
<td>3,180</td>
</tr>
</tbody>
</table>
### Summary Statistics (PSID Sample)

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.794</td>
<td>10.27</td>
</tr>
<tr>
<td>Male</td>
<td>0.808</td>
<td>0.39</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.059</td>
<td>0.24</td>
</tr>
<tr>
<td>Year</td>
<td>1985</td>
<td>7.62</td>
</tr>
<tr>
<td>Log Consumption</td>
<td>8.199</td>
<td>0.65</td>
</tr>
<tr>
<td>Log Expenditure Needs</td>
<td>8.124</td>
<td>0.32</td>
</tr>
<tr>
<td>Consumption growth ((\log(c_{t,2})-\log(c_{t,1})))</td>
<td>0.049</td>
<td>0.360</td>
</tr>
</tbody>
</table>

#### Sample Size

- Number of Observations: 80,984
- Number of Households: 11,055