

Part 2: Market Imperfections

Nathaniel Hendren

Harvard and NBER¹

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¹Thanks to Raj Chetty and Amy Finkelstein for generously providing their lecture notes, some of which are reproduced here

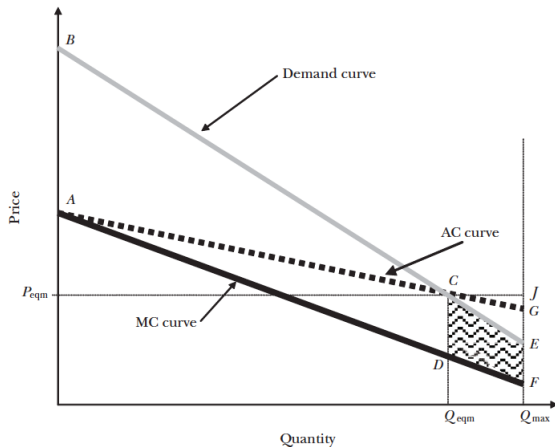
- 1 The Akerlof Model
- 2 The Screening Model
- 3 Private Information versus Adverse Selection
- 4 Public Health Insurance
- 5 Public/Private Crowd Out
- 6 Dynamic Insurance

Review of Akerlof (1970) (Applied to Insurance)

- Consider binary decision to purchase insurance
- People differ in their expected costs to an insurer
- Those with higher expected costs have higher demand for insurance
- Competitive equilibrium \rightarrow marginal purchaser covers average cost of higher risks

Akerlof Competitive Equilibrium (from EF2011, JEP)

Figure 1
Adverse Selection in the Textbook Setting



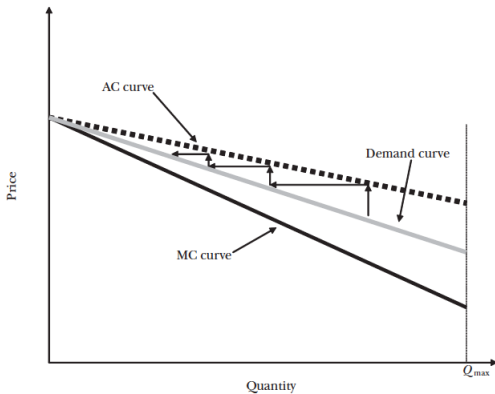
Source: Einav and Finkelstein (2011 JEP)

- Not clear that competitive equilibrium involves any insurance
 - Market can “unravel”
 - Market unravels if no one is willing to pay the pooled cost of those with higher demand (and thus likely to be higher risk)

Akerlof Unraveling

Figure 2 (continued)

B: Adverse Selection with Complete Unraveling

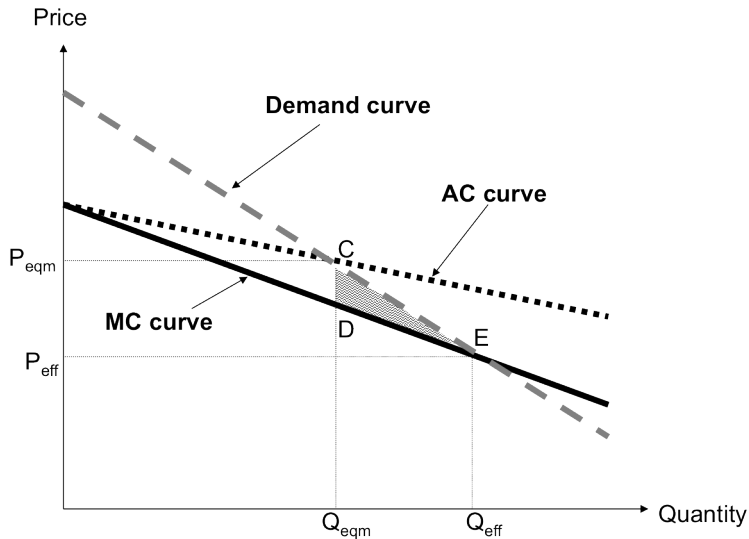


Source: Einav and Finkelstein (2011 JEP)

Modeling Welfare Impact of Adverse Selection

- “Textbook” model provided in Einav and Finkelstein (JEP 2011)
- Suppose there are two (fixed) insurance contracts:
 - High coverage (H) and low coverage (L)
- Agents choose H or L
 - P is relative price of H versus L
 - $D(p)$ is the demand curve
 - Fraction of people who purchase H instead of L
 - $AC(p)$ is the average cost curve
 - $MC(p)$ is the marginal cost curve

Competitive Equilibrium with Adverse Selection



Source: Einav, Finkelstein, and Cullen (2010)

Empirical Implementation: Einav, Finkelstein, and Cullen (2010 QJE)

- Need random variation in prices
 - Can estimate BOTH demand and cost curve
 - Demand = fraction that buy at posted price
 - Cost = added cost on policy H versus L for those who purchase at posted price
 - Rarely does price variation identify both supply + demand!
- But need some institutional structure that randomly varies prices...
 - Alcoa! (they make aluminum)
 - Business unit heads choose price charged for high versus low coverage plans

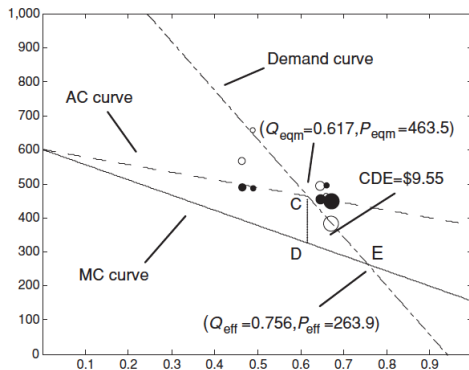


FIGURE V
Efficiency Cost of Adverse Selection—Empirical Analog

Source: Einav, Finkelstein, and Cullen (2010)

Results (II)

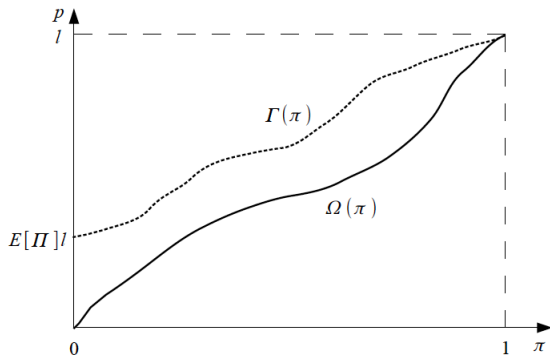
- Results suggest welfare loss is “small”
 - \$9.55/employee (~2% of the average price)
- Beautiful paper - strong link between theory and empirics
- Caveats:
 - Only studies welfare loss from inefficient pricing
 - Perhaps the contracts were inefficient? (Rothschild and Stiglitz 1976)
 - Generalizeability?
 - Productively employed upper-middle class
 - Group vs. individual insurance
 - Intensive margin: more vs. less insurance, instead of insurance vs. no insurance
- Modeling issue: does a competitive equilibrium actually exist?
 - Not clear...companies can choose price levels and price difference...

Empirical Implementation: Multiple Equilibria (Smetters and Scheuer 2014)

- In principle, there are many potential intersections of demand and cost curves
- Potential for multiple equilibria?
- Can this explain worry about Obamacare website?

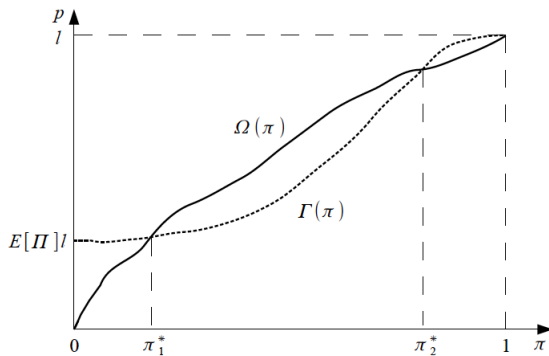
Full Unraveling

Figure 1: Unique Competitive Equilibrium with Complete Unraveling



Multiple Equilibria

Figure 2: Multiple Competitive Equilibria



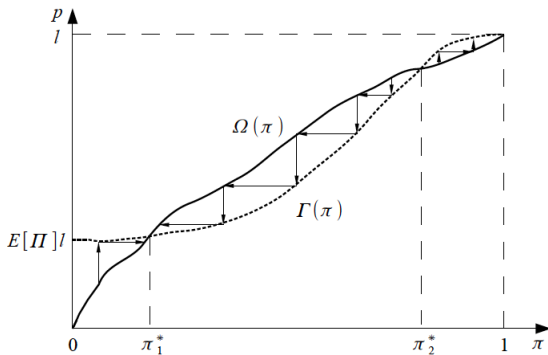
Choosing Equilibria

- Standard Theory Approach:
- Two stage game:
 - ① Firm chooses prices forecasting demand
 - ② Consumers choose insurance
- Prove: This generates π_1^* as the outcome

Why might initial conditions matter?

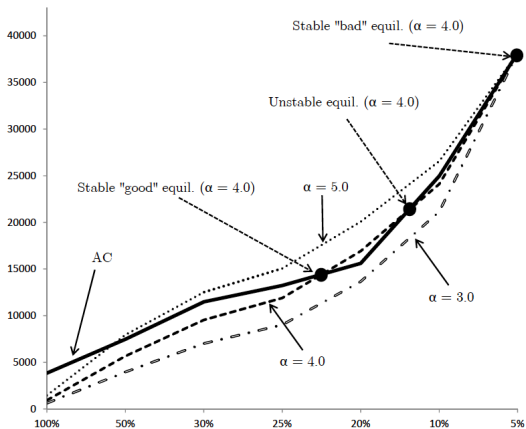
- Suppose insurers have limited information
- Assumption: Firms raise their price when they have negative profits

Figure 3: Dynamics and Equilibrium Stability



Calibration using MEPS

Figure 4: Willingness to Pay and Average Costs: Median Net Worth



Source: Medical Expenditure Panel Survey (Cohen and Uberoi 2013).

Explanation: Wealth equals net worth (assets less liabilities), including net housing wealth.

- Harvard offers PPO and HMO
- Traditionally, subsidizes the more expensive PPO plan
- In 1995, switches to voucher system that provides equal payment to PPO and HMO
 - Individuals bore full average cost of PPO relative to HMO
 - Induced significant adverse selection
 - PPO unraveled

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- Screening theory: Like Mirrlees but with two distinctions:
 - Participation constraint
 - Competition between insurers
- Papers
 - Rothschild and Stiglitz (1976)
 - Wilson (1977)
 - Riley (1979)
 - Spence (1978)
 - More recently: Netzer and Scheuer (2012); Mimra and Wambach (2011)

Rothschild and Stiglitz (1976)

- Relax the contract space (premium & copay)
- But restrict to two types, binary loss event
- Results:
 - High risk type gets full insurance
 - Low risk type is under-insured (has higher “copay”)
 - Competitive equilibrium cannot sustain cross-subsidization across types
 - Contrasts with Akerlof’s model in which marginal type was subsidizing
 - Market may “unravel” in a different sense
 - Competitive equilibrium doesn’t exist if the low type wants to subsidize bad risk type to get more insurance
- Prescott and Townsend (1984) show that this problem with non-existence and sub-optimality is quite general with private information
- Equilibrium may not exist

“Solutions” to Non-Existence Problem

- How bad is the non-existence problem?
 - Generic (Riley 1979; Hendren 2014)
- Solutions to get pure strategies
 - Wilson (1977)
 - Riley (1979)
 - Spence (1978)
 - More recently: Netzer and Scheuer (2012); Mimra and Wambach (2011)
- (Mixed strategies – Maskin 1985)

Wilson (1977) and Riley (1979)

- Wilson proposes the following two stage game:
 - Firms post insurance contracts
 - Firms view other firms contracts and can react by dropping one of their (unprofitable) contracts
- Riley proposes the following two stage game
 - Firms post insurance contracts
 - Firms view other firms contracts and can react by adding (but not dropping) contracts

Empirical Test: Positive Correlation Test

- Chiappori and Salanie (2000)
 - Asymmetric information -> positive correlation between claims and coverage
 - Holds in both Wilson (1977) and Riley (1979)
 - Is there a positive correlation between insurance purchase and insurance claims?

- Specification:

$$INS = \beta X + \epsilon$$

$$COST = \Gamma X + \eta$$

- Test: $cov(\epsilon, \eta) \neq 0$
- Data: Auto insurance company
- Key: control flexibly for X s
- Find no evidence of adverse selection

Empirical Test: Finkelstein and Poterba (2004)

- Finkelstein and Poterba study annuities in the UK
- Specification

$$Cost = \gamma INS + \beta X + \epsilon$$

- Find no evidence of INS quantity; but evidence on guarantee amount

Limitations of Positive Correlation Test: Preference Heterogeneity

- Standard theory: people differ only in their risk type
 - Different expected costs to the insurer
- Reality: People are different in many other ways too
 - Cost to the insurer may not be only driver of demand
- Preference heterogeneity may not be independent of risk type
 - The “worried well” may help sustain insurance markets
 - Could lead to “advantageous selection” instead of adverse selection

- Many papers find evidence that preferences other than risk type affect demand
- Finkelstein and McGarry (2006, AER) document that seat-belt use and income are correlated with LTC insurance purchase
 - Suggest this could explain why we see no adverse selection in LTC

Table 1

TABLE 1—RELATIONSHIP BETWEEN INDIVIDUAL BELIEFS AND SUBSEQUENT NURSING HOME USE

	No controls (1)	Control for insurance company prediction		Control for application information (4)
		(2)	(3)	
Individual prediction	0.091*** (0.021)		0.043** (0.020)	0.037* (0.019)
Insurance company prediction		0.400*** (0.020)	0.395*** (0.021)	
pseudo- R^2	0.005	0.097	0.099	0.183
N	5,072	5,072	5,072	4,780

Notes: Reported coefficients are marginal effects from probit estimation of equation (1). Dependent variable is an indicator for any nursing home use from 1995 through 2000 (mean is 0.16). Both individual and insurance company predictions are measured in 1995. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1-percent, 5-percent, and 10-percent level, respectively. Column 4—which includes controls for “application information”—includes controls for age (in single year dummies), sex, marital status, age of spouse, over-35 health indicators, and a complete set of two-way and three-way interactions for all of the variables used in the insurance company prediction (age dummies, sex, limitations to activities of daily living, limitations to instrumental activities of daily living, and cognitive impairment); see text for more details.

Table 2

TABLE 2—RELATIONSHIP BETWEEN INDIVIDUAL BELIEFS AND INSURANCE COVERAGE

	No controls (1)	Control for insurance company prediction		Control for application information (4)
		(2)	(3)	
Individual prediction	0.086*** (0.017)		0.099*** (0.017)	0.083*** (0.016)
Insurance company prediction		-0.125*** (0.023)	-0.140*** (0.023)	
pseudo- R^2	0.007	0.010	0.019	0.079
N	5,072	5,072	5,072	4,780

Notes: Reported coefficients are marginal effects from probit estimation of equation (2). Dependent variable is an indicator for whether individual has long-term care insurance coverage in 1995 (mean is 0.11). Both individual and insurance company predictions are measured in 1995. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1-percent, 5-percent, and 10-percent level, respectively. Column 4—which includes controls for “application information”—includes controls for age (in single year dummies), sex, marital status, age of spouse, over-35 health indicators, and a complete set of two-way and three-way interactions for all of the variables used in the insurance company prediction (age dummies, sex, limitations to activities of daily living, limitations to instrumental activities of daily living, and cognitive impairment); see text for more details.

Table 3

TABLE 3—THE RELATIONSHIP BETWEEN LONG-TERM CARE INSURANCE AND NURSING HOME ENTRY

	No controls (1)	Controls for insurance company prediction (2)	Controls for application information (3)
Correlation coefficient from bivariate probit of LTCINS and CARE	-0.105***	-0.047	-0.028
	(<i>p</i> = 0.006)	(<i>p</i> = 0.25)	(<i>p</i> = 0.51)
Coefficient from probit of CARE on LTCINS	-0.046***	-0.021	-0.014
	(0.015)	(0.016)	(0.016)
<i>N</i>	5,072	5,072	4,780

Notes: Top row reports the correlation of the residual from estimation of a bivariate probit of any nursing home use (1995–2000) and long-term care insurance coverage (1995); *p* values are given in parentheses. Bottom row reports marginal effect on indicator variable for long-term care insurance in 1995 from probit estimation of equation (3). The dependent variable is an indicator variable for any nursing home use from 1995 through 2000; heteroskedasticity-adjusted robust standard errors are in parentheses. For all rows, control variables are described in column headings; see text for more information. ***, **, * denote statistical significance at the 1-percent, 5-percent, and 10-percent level, respectively. Means of CARE and LTCINS are 0.16 and 0.11, respectively.

Table 4

TABLE 4—RELATIONSHIP BETWEEN LTCINS AND CARE
(Sample restricted to individuals with same choice set)

	No controls (1)	Controls for insurance company prediction (2)	Controls for application information (3)
Correlation coefficient from bivariate probit of LTCINS and CARE	-0.123* (<i>p</i> = 0.08)	-0.122* (<i>p</i> = 0.10)	-0.191** (<i>p</i> = 0.017)
Coefficient from regression of CARE on LTCINS	-0.032* (0.018)	-0.028* (0.015)	-0.033** (0.012)
<i>N</i>	1,504	1,504	1,438

Notes: Sample is limited to individuals in the top quartile of the wealth and income distribution and who have none of the health characteristics that might make them ineligible for private insurance. Top row reports the correlation of the residual from estimation of a bivariate probit of any nursing home use (1995–2000) and long-term care insurance coverage (1995); *p* values are given in parentheses. Bottom row reports marginal effect on indicator variable for long-term care insurance in 1995 from probit estimation in equation (3). The dependent variable is an indicator variable for any nursing home use from 1995 through 2000; heteroskedasticity-adjusted robust standard errors are in parentheses. For all rows, control variables are described in column headings; see text for more information. ***, **, * denote statistical significance at the 1-percent, 5-percent, and 10-percent level, respectively. Means of CARE and LTCINS are 0.09 and 0.17, respectively.

Table 5

TABLE 5—PREFERENCE-BASED SELECTION

	No controls		Control for insurance company prediction		Control for application information	
	NH Entry (1)	LTC Insurance (2)	NH Entry (3)	LTC Insurance (4)	NH Entry (5)	LTC Insurance (6)
Panel A: Wealth						
Top wealth quartile	-0.095*** (0.013)	0.150*** (0.020)	-0.038** (0.014)	0.131*** (0.020)	-0.018 (0.015)	0.139*** (0.022)
Wealth quartile 2	-0.073*** (0.013)	0.104*** (0.020)	-0.025* (0.014)	0.089*** (0.020)	-0.013 (0.014)	0.092*** (0.020)
Wealth quartile 3	-0.030** (0.015)	0.062*** (0.020)	0.0004 (0.016)	0.052*** (0.019)	0.006 (0.015)	0.057*** (0.020)
Bottom wealth quartile (omitted)	—	—	—	—	—	—
Individual prediction	0.086*** (0.021)	0.089*** (0.017)	0.042** (0.020)	0.098*** (0.017)	0.035* (0.019)	0.086*** (0.017)
Panel B: Preventive health activity						
Preventive activity	-0.106*** (0.0118)	0.066*** (0.017)	-0.054*** (0.018)	0.052*** (0.017)	-0.016 (0.019)	0.016 (0.017)
Individual prediction	0.095*** (0.021)	0.082*** (0.017)	0.047** (0.020)	0.095*** (0.017)	0.037* (0.020)	0.082*** (0.017)
Panel C: Seat belt use						
Always wear seatbelt	-0.059*** (0.014)	0.053*** (0.010)	-0.031** (0.013)	0.048*** (0.010)	-0.018 (0.012)	0.029*** (0.010)
Individual prediction	0.092*** (0.021)	0.084*** (0.017)	0.044** (0.020)	0.097*** (0.017)	0.038* (0.019)	0.082*** (0.016)

Notes: Table reports marginal effects from probit estimation of equations (1) and (2). Additional controls are given in column headings; see text for more information. In panel A, omitted wealth category is quartile 4. For panel A, income controls are omitted from the “application information” controls since they are highly multi-collinear with assets. In panel B, “preventive activity” measures the proportion of gender-appropriate preventive health behaviors undertaken; all estimates in panel B include an additional control for gender. Heteroskedasticity-adjusted robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1-percent, 5-percent, and 10-percent level, respectively.

- Fan et al (2008, JPE) document advantageous selection in MediGap
- Use HRS and MCBS
- MCBS contains detailed cost information

TABLE 2
ORDINARY LEAST SQUARES REGRESSION RESULTS OF TOTAL MEDICAL EXPENDITURE ON
“MEDIGAP” COVERAGE IN THE MCBS

VARIABLE	A. WITHOUT HEALTH CONTROLS			B. WITH DIRECT HEALTH CONTROLS		
	All (1)	Female (2)	Male (3)	All (4)	Female (5)	Male (6)
Medigap	-4,392.7*** (346.5)	-6,037.4*** (455.5)	-1,863.4*** (538.8)	1,937.0*** (257.2)	1,677.3*** (348.0)	2,420.9*** (395.8)
Female	270.0 (356.2)	-751.6*** (283.3)
Age - 65	387.5*** (138.0)	460.6*** (175.5)	292.9 (228.5)	394.5*** (117.2)	417.5*** (144.6)	355.4* (196.8)
(Age - 65) ²	1.9 (10.6)	-1.8 (13.2)	5.6 (18.8)	-27.5*** (9.2)	-32.0*** (11.4)	-22.8 (16.2)
(Age - 65) ³	.12 (.22)	.17 (.27)	.07 (.43)	.47** (.21)	.55** (.25)	.47 (.38)
State dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,945	9,725	6,220	14,129	8,371	5,758
Adjusted R ²	.073	.092	.060	.211	.196	.252

NOTE.—The dependent variable is total medical expenditure. All regressions are weighted by the cross-section sample weights. Health controls included in panel B are described in detail in the Data Appendix under the category Health. A total of 71 health indicators are included. Robust standard errors clustered at the individual level are in parentheses.

* Significant at 10 percent.

** Significant at 5 percent.

*** Significant at 1 percent.

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Private Information vs. Adverse Selection

- General impression suggests adverse selection is not a big issue with insurance markets
 - Welfare losses are generally found to be small (Einav Finkelstein and Levin 2010)
- Not much evidence of massive amounts of adverse selection...
- But, is adverse selection the right thing to look for?
 - Akerlof (1970) suggests private info can completely unravel the market
 - Would not observe positive correlation between insurance purchase and claims if people with private information aren't offered any contracts

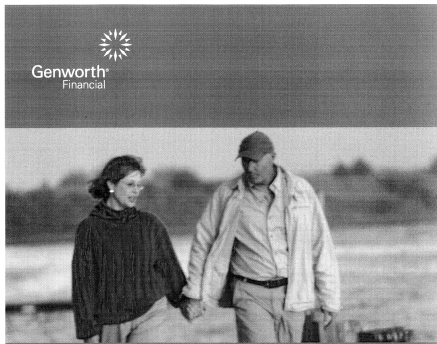
Model of Private Information

- Hendren (2013) characterizes when private information leads to adverse selection
- Depends on two numbers:
 - Markup people are willing to pay for insurance, WTP
 - Smallest markup imposed by worse risks adversely selecting the insurance contract
 - “Price of market existence”, p_{info}
- When $WTP \leq p_{info}$, insurance contracts would be so heavily adversely selected that they cannot earn positive profits
 - Market shuts down when private info problem too big
 - Adverse selection not a robust empirical implication of private information
- Is the private information problem ever this bad?

Hendren (2013) studies insurance rejections

- 1 in 7 applicants rejected in individual health insurance
- Rejections common in individual life, LTC, disability insurance too
- Lots of policy interest...
 - Even Romney wanted to ban rejections for pre-existing conditions
- Idea: Rejections are market segments (defined by observable characteristics) for which private information has led to market unraveling

Underwriting Guidelines



Genworth
Financial

**LONG TERM CARE INSURANCE
UNDERWRITING GUIDE**

PROVIDED BY THE GENWORTH UNDERWRITING DEPARTMENT

Long Term Care Insurance Underwritten
by Genworth Life Insurance Company,
and in New York
by Genworth Life Insurance Company of New York
Administrative Offices: Richmond, VA.

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Not for use with
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UNINSURABLE CONDITIONS

Acquired Immune Deficiency Syndrome (AIDS)
ADL limitation, present
AIDS Related Complex (ARC)
Alzheimer's Disease
Amputation due to disease, e.g., diabetes or atherosclerosis
Amyotrophic Lateral Sclerosis (ALS), Lou Gehrig's Disease
Ascites present
Ataxia, Cerebellar
Autonomic Insufficiency (Shy-Drager Syndrome)
Autonomic Neuropathy (excluding impotence)
Bahçet's Disease
Binowanger's Disease
Bladder incontinence requiring assistance
Blindness due to disease or with ADL/IADL limitations
Bowel incontinence requiring assistance
Buerger's Disease (Thromboangiitis obliterans)
Cerebral Vascular Accident (CVA)
Chorea
Chronic Memory Loss
Cognitive Testing, failed
Cystic Fibrosis
Dementia
Diabetes treated with insulin
Dialysis, Kidney (Renal)
Ehlers-Danlos Syndrome
Forgetfulness (frequent or persistent)
Gangrene due to diabetes or peripheral vascular disease
Hemiplegia
Hoyer Lift
Huntington's or other forms of Chorea
Immune Deficiency Syndrome
Korsakoff's Psychosis
Leukemia-except for Chronic Lymphocytic Leukemia (CLL) and Hairy Cell Leukemia (HCL)
Marfan's Syndrome
Medications
 Antabuse (disulfiram)
 Aripiprazole (donapexil HCl)
 Cempra (acamprosate calcium)
 Cogrex (tacrine)
 Depo (naltrexone)
 Eaxton (investigative)
 Hydrogine (ergoloid mesylate)
 Namenda (memantine)
 Razadyne (galantamine hydrobromide)
 Rennyl (galantamine hydrobromide)
 ReVia (naltrexone)
 Vivtrol (naltrexone)
Memory Loss, chronic
Mesothelioma
Multiple Sclerosis (MS)

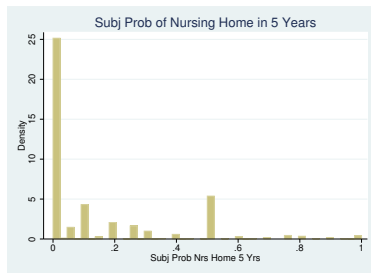
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Estimating Private Information

- Does private information cause rejections?
- Need to estimate private information for rejectees and non-rejectees.
 - Positive correlation test fails
 - Difficult to estimate demand curves for contracts that don't exist
- Solution: Use subjective probability elicitations in the Health and Retirement Study
 - “What’s the chance (0-100%) that you will go to a nursing home in the next 5 years?”

Elicitation Error

- Do people report their true beliefs?
 - Hendren (2013) argues probably not
 - See Manski (ECMA 2004) for a rosier assessment
 - Evidence from psychology shows question framing affects response



- Zero is pretty optimistic for 75 year olds...

Solution: Elicitations as “Noisy” measures of beliefs

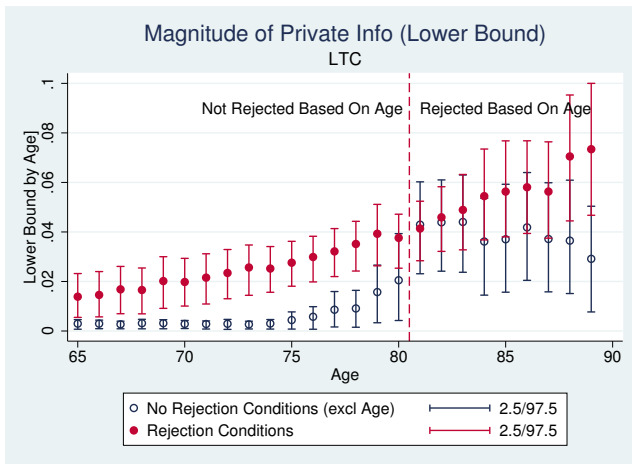
- Hendren (2013) imposes increasing sets of assumptions
 - Minimal assumptions allow for testing for presence of private information
 - Stronger assumptions allow for quantification of price of market existence
- General tradeoff between quality of question vs. quality of assumptions

Assumptions on Beliefs (I)

- General idea: Agents behave as if they have beliefs P about the loss L , but may not be able to express these beliefs on surveys
 - Savage (1954) axioms; see Blackwell (1951, 1953) for sufficient statistics work too...
- **Assumption 1:** Elicitations contain no more information about L than do true beliefs
 - If Z contains information about L conditional on X , then so does P .
 - " P is sufficient statistic for Z about L ".
- **Test for Private Information:** Is Z predictive of L , conditional on X ?
- Context: Tests for private information in hypothetical insurance market that pays \$1 in the event L occurs.

Lower Bound Test

	LTC	Disability	Life
Reject p-value ²	0.0358*** (0.000)	0.0512*** (0.000)	0.0587*** (0.000)
No Reject p-value ²	0.0049 (0.336)	0.0240 (0.853)	0.0249 (0.119)
Difference: Δ_z p-value ³	0.0309*** (0.000)	0.0272 (0.121)	0.0338*** (0.000)
Uncertain, $E[m_z(P_z)]$ (p-value)	0.0086*** (0.001)	0.0409*** (0.000)	0.0294*** (0.000)



- Evidence of private information
 - Is it sufficient to explain absence of trade for the rejected?
 - Small enough to explain presence of trade for those not rejected
- Need additional assumptions...
 - Unbiased beliefs
 - Model of the elicitation error

Tax Rate Equivalence: $\inf T(p) - 1$

	LTC	Disability	Life
Reject	0.827**	0.661**	0.428**
5%	0.657	0.524	0.076
95%	1.047	0.824	0.780
No Reject	0.163	0.069	0.350
5%	0.000	0.000	0.000
95%	0.361	0.840	0.702
Difference	0.664**	0.592**	0.077
5%	0.428	0.177	-0.329
95%	0.901	1.008	0.535

What is a plausible willingness to pay?

- Existing estimates/calibrations of $\frac{u'(w-l)}{u'(w)}$:
 - LTC: 26-62% (Brown and Finkelstein, 2008)
 - Disability: 46-109% (Bound et al., 2004)
- Direct Calibration: Assume $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$ and $l = \gamma w$
 - If $\gamma = 10\%$ and $\sigma = 3$, then $\frac{u'(w-l)}{u'(w)} - 1 = 0.372$

Comparison to Positive Correlation Test

- Existing literature has conducted versions of the positive correlation test in LTC and Life
 - Finkelstein and McGarry (AER 2006) find no evidence of adverse selection in LTC
 - But were first to use subj prob to show people know about their future nursing home use
 - Suggest inversely correlated unobserved preference heterogeneity as explanation for why private info does not manifest in adverse selection (see also Cutler et al 2008 AER P&P, Fang et al (2008))
 - Cawley and Philipson (JPE 1999) find no evidence of adverse selection in Life
 - Suggest insurance company knows more than applicants
 - He (2008 JPubEc) revisits Life and finds some evidence of adverse selection
- Results suggest practice of rejections limits the extent of adverse selection in these markets
 - Positive correlation test only tests for adverse selection, not private information

Thoughts on Ideas for Future Work

- Group versus individual markets
 - Matching?
- Financial markets
 - Large literature on auctions...little empirical literature on CDOs, ABS, etc
 - Why do these markets freeze in crisis?
- Dynamic Selection (Reclassification risk)

- 1 The Akerlof Model
- 2 The Screening Model
- 3 Private Information versus Adverse Selection
- 4 Public Health Insurance**
- 5 Public/Private Crowd Out
- 6 Dynamic Insurance

Moral Hazard - key aspect of existing literature.

-why do we care about 'moral hazard'? fiscal externality logic

RAND experiment

Elasticity of 0.2 (1% change in price leads to 0.2% change in total costs)

Oregon Lottery

- In 2008, Oregon ran a lottery for Medicaid
 - Budget for 10K
 - 90K signed up; drew 30K for 10K slots

Oregon Health Insurance Experiment

TABLE IV
HOSPITAL UTILIZATION

	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)
Panel A: Extensive margin				
All hospital admissions	0.067 (0.250)	0.0054 (0.0019)	0.021 (0.0074)	[0.004]
Admissions through ER	0.048 (0.214)	0.0018 (0.0016)	0.0070 (0.0062)	[0.265]
Admissions not through ER	0.029 (0.167)	0.0041 (0.0013)	0.016 (0.0051)	[0.002]
Panel B: All hospital admissions				
Days	0.498 (3.795)	0.026 (0.027)	0.101 (0.104)	[0.329] {0.328}
List charges	2,613 (19,942)	258 (146)	1,009 (569)	[0.077] {0.106}
Procedures	0.155 (1.08)	0.018 (0.0083)	0.070 (0.032)	[0.031] {0.059}
Standardized treatment effect		0.012 (0.0067)	0.047 (0.026)	[0.073]

Oregon Health Insurance Experiment

Panel C: Admissions through ER

Days	0.299 (2.326)	0.023 (0.017)	0.089 (0.067)	[0.183] [0.187]
List charges	1,502 (12,749)	163 (96)	636 (376)	[0.091] [0.171]
Procedures	0.081 (0.694)	0.0080 (0.0054)	0.031 (0.021)	[0.135] [0.187]
Standardized treatment effect		0.011 (0.0069)	0.044 (0.027)	[0.100]

Panel D: Admissions not through ER

Days	0.199 (2.38)	0.0033 (0.017)	0.013 (0.065)	[0.841] [0.842]
List charges	1,110 (12,422)	98 (91)	384 (356)	[0.281] [0.383]
Procedures	0.075 (0.708)	0.010 (0.0056)	0.038 (0.022)	[0.080] [0.162]
Standardized treatment effect		0.0077 (0.0068)	0.030 (0.026)	[0.254]

Oregon Health Insurance Experiment

TABLE V
HEALTH CARE UTILIZATION (SURVEY DATA)

	Extensive margin (any)				Total utilization (number)			
	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)	Control mean (5)	ITT (6)	LATE (7)	<i>p</i> -values (8)
Prescription drugs currently	0.637 (0.481)	0.025 (0.0083)	0.088 (0.029)	[0.002] {0.005}	2.318 (2.878)	0.100 (0.051)	0.347 (0.176)	[0.049] {0.137}
Outpatient visits last six months	0.574 (0.494)	0.062 (0.0074)	0.212 (0.025)	[<0.0001] {<0.0001}	1.914 (3.087)	0.314 (0.054)	1.083 (0.182)	[<0.0001] {<0.0001}
ER visits last six months	0.261 (0.439)	0.0065 (0.0067)	0.022 (0.023)	[0.335] {0.547}	0.47 (1.037)	0.0074 (0.016)	0.026 (0.056)	[0.645] {0.643}
Inpatient hospital admissions last six months	0.072 (0.259)	0.0022 (0.0040)	0.0077 (0.014)	[0.572] {0.570}	0.097 (0.4)	0.0062 (0.0062)	0.021 (0.021)	[0.311] {0.510}
Standardized treatment effect		0.050 (0.011)	0.173 (0.036)	[<0.0001]		0.040 (0.011)	0.137 (0.038)	[0.0003]
Annual spending ^a					3,156	226 (108)	778 (371)	[0.037]

Notes. Standard errors in parentheses; per comparison *p*-values in square brackets; family-wise *p*-values in curly brackets. Hospital admissions exclude childbirth. Columns (2) and (6) report the coefficient and standard error on *LOTTERY* from estimating equation (1) by OLS. Columns (3) and (7) report the coefficient and standard error on *INSURANCE* from estimating equation (3) by IV; for the IV estimates in column (3), the endogenous variable *INSURANCE* is defined as "ever on Medicaid" during our study period and the first stage is given in the first row of Table III. Columns (4) and (8) report the per-comparison *p*-value and the family-wise *p*-value across the four different measures of utilization used to create the standardized treatment effect. Standardized treatment effect reports results based on equation (2). All regressions include household size fixed effects, survey wave fixed effects, and the interaction between the two. All standard errors are clustered on the household and all regressions are weighted using survey weights. Sample consists of survey responders ($N=23,741$).

^aTo calculate the implied spending effects associated with the estimated utilization effects, we use data from the 2002–2007 (pooled) Medical Expenditure Panel Survey (MEPS) on expenditures of all nonelderly (age 19–64) adults below 100% of poverty who are publicly insured. This gives us a total sample of over 7,500 individuals. We use their expenditures (all inflated with the CPI-U to 2007 dollars) to calculate average expenditures per outpatient visit, average expenditures per ER visit, average expenditures per inpatient visit (for visits not related to childbirth), and average semi-annual (six-month) spending on prescription drug. All spending is total expenditures (i.e., not just insured) expenditures. The underlying costs are \$150 per outpatient visit, \$435 per ER visit, \$7,523 per inpatient visit, and \$156 six-month expenditure per current prescription drug; we multiply these all by two to get annual costs.

Oregon Health Insurance Experiment

TABLE VI
COMPLIANCE WITH RECOMMENDED PREVENTIVE CARE (SURVEY DATA)

	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)
Blood cholesterol checked (ever)	0.625 (0.484)	0.033 (0.0074)	0.114 (0.026)	[<0.0001] [<0.0001]
Blood tested for high blood sugar/diabetes (ever)	0.604 (0.489)	0.026 (0.0074)	0.090 (0.026)	[0.0004] [<0.0001]
Mammogram within last 12 months (women ≥ 40)	0.298 (0.457)	0.055 (0.012)	0.187 (0.04)	[<0.0001] [<0.0001]
Pap test within last 12 months (women)	0.406 (0.491)	0.051 (0.01)	0.183 (0.034)	[<0.0001] [<0.0001]
Standardized treatment effect		0.087 (0.012)	0.300 (0.041)	[<0.0001]

Notes. Standard errors in parentheses; per comparison *p*-values in square brackets; family-wise *p*-values in curly brackets. Column (2) reports the coefficient and standard error on *LOTTERY* from estimating equation (1) by OLS. Column (2) reports the coefficient and standard error on *INSURANCE* from estimating equation (3) by IV; for the IV estimates in column (3), the endogenous variable *INSURANCE* is defined as “ever on Medicaid” during our study period and the first stage is given in the first row of Table III. Column (4) reports the per comparison *p*-value and the family-wise *p*-value across the four different preventive care measures used to create the standardized treatment effect. Standardized treatment effect reports results based on equation (2). All regressions include household size fixed effects, survey wave fixed effects, and the interaction between the two. All standard errors are clustered on the household and all regressions are weighted using survey weights. Sample consists of survey responders ($N=23,741$).

Oregon Health Insurance Experiment

TABLE VII
FINANCIAL STRAIN (ADMINISTRATIVE DATA)

	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)
Panel A: Overall				
Any bankruptcy	0.014 (0.119)	0.0022 (0.0014)	0.0086 (0.0053)	[0.106] [0.358]
Any lien	0.021 (0.144)	0.0012 (0.0014)	0.0047 (0.0056)	[0.406] [0.698]
Any judgment	0.064 (0.244)	0.0014 (0.0024)	0.0054 (0.010)	[0.573] [0.698]
Any collection	0.500 (0.500)	-0.012 (0.0041)	-0.048 (0.016)	[0.003] [0.013]
Any delinquency (credit accounts)	0.366 (0.482)	0.0016 (0.0042)	0.0063 (0.017)	[0.704] [0.698]
Standardized treatment effect		0.0022 (0.0049)	0.0086 (0.019)	[0.653]
Panel B: Medical debt				
Any medical collection	0.281 (0.449)	-0.016 (0.0040)	-0.064 (0.016)	[<0.0001] [<0.0001]
Amount owed in medical collections	1,999 (6733)	-99 (45)	-390 (177)	[0.028] [0.025]
Standardized treatment effect		-0.026 (0.0061)	-0.100 (0.024)	[<0.0001]
Panel C: Nonmedical debt				
Any nonmedical collection	0.392 (0.488)	-0.0046 (0.0041)	-0.018 (0.016)	[0.264] [0.455]
Amount owed in nonmedical collections	2,740 (9,492)	-20 (63)	-79 (248)	[0.751] [0.752]
Standardized treatment effect		-0.0058 (0.0059)	-0.023 (0.023)	[0.325]

TABLE VIII
FINANCIAL STRAIN (SURVEY DATA)

	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)
Any out of pocket medical expenses, last six months	0.555 (0.497)	-0.058 (0.0077)	-0.200 (0.026)	[<0.0001] {<0.0001}
Owe money for medical expenses currently	0.597 (0.491)	-0.052 (0.0076)	-0.180 (0.026)	[<0.0001] {<0.0001}
Borrowed money or skipped other bills to pay medical bills, last six months	0.364 (0.481)	-0.045 (0.0073)	-0.154 (0.025)	[<0.0001] {<0.0001}
Refused treatment because of med- ical debt, last six months	0.081 (0.273)	-0.011 (0.0041)	-0.036 (0.014)	[0.01] {0.01}
Standardized treatment effect		-0.089 (0.010)	-0.305 (0.035)	[<0.0001]

Oregon Health Insurance Experiment

B

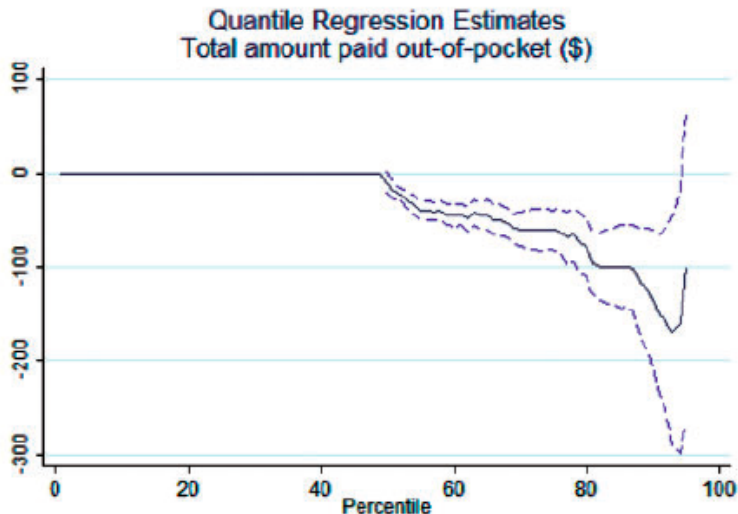


FIGURE I

Oregon Health Insurance Experiment

TABLE IX
HEALTH

	Control mean (1)	ITT (2)	LATE (3)	<i>p</i> -values (4)
Panel A: Administrative data				
Alive	0.992 (0.092)	0.00032 (0.00068)	0.0013 (0.0027)	[0.638]
Panel B: Survey data				
Self-reported health good/very good/excellent (not fair or poor)	0.548 (0.498)	0.039 (0.0076)	0.133 (0.026)	[<0.0001] {<0.0001}
Self-reported health not poor (fair, good, very good, or excellent)	0.86 (0.347)	0.029 (0.0051)	0.099 (0.018)	[<0.0001] {<0.0001}
Health about the same or gotten better over last six months	0.714 (0.452)	0.033 (0.0067)	0.113 (0.023)	[<0.0001] {<0.0001}
# of days physical health good, past 30 days*	21.862 (10.384)	0.381 (0.162)	1.317 (0.563)	[0.019] {0.018}
# days poor physical or mental health did not impair usual activity, past 30 days*	20.329 (10.939)	0.459 (0.175)	1.585 (0.606)	[0.009] {0.015}
# of days mental health good, past 30 days*	18.738 (11.445)	0.603 (0.184)	2.082 (0.64)	[0.001] {0.003}
Did not screen positive for depression, last two weeks	0.671 (0.470)	0.023 (0.0071)	0.078 (0.025)	[0.001] {0.003}
Standardized treatment effect		0.059 (0.011)	0.203 (0.039)	[<0.0001]

Notes. Standard errors in parentheses; per comparison *p*-values in square brackets; family-wise *p*-values in curly brackets. Column (2) reports the coefficient and standard error on *LOTTERY* from estimating equation (1) by OLS. Column (3) reports the coefficient and standard error on *INSURANCE* from estimating equation (3) by IV; for the IV estimates in column (3), the endogenous variable *INSURANCE* is defined as “ever on Medicaid” during our study period and the first stage is given in the first row of Table III. Column (4) reports the per comparison *p*-value and the family-wise *p*-value across the different measures used to create the standardized treatment effect. Standardized treatment effect reports results based on equation (2). All regressions include household size fixed effects and standard errors are clustered on the household. The regressions in Panel A include lottery draw fixed effects, and the dependent variable “alive” is measured from the notification date through September 2009 ($N = 74,922$). The regressions in Panel B include survey wave fixed effects and the interaction of survey wave fixed effects with household size fixed effects, and are weighted using the survey weights ($N = 23,741$).

- How should we think about the welfare impact?
 - Subjective health?
- Impact of Oregon HIE on labor supply
- Why do we care? Fiscal externality...
- Does the experiment capture the relevant impact?

Table 1: 2009 Earnings

	Control Mean	ITT	LATE	p-values
	(1)	(2)	(3)	(4)
Employment (Any Earnings)	0.547	-0.0042 (0.0037)	-0.016 (0.014)	0.266
Amount of Earnings	6513.015 (10227.3)	-51.74 (76.8)	-194.93 (289.0)	0.500
Earnings above FPL	0.131	-0.0032 (0.0026)	-0.012 (0.0099)	0.219

Medicaid on Labor Supply

Table 2: 2009 Benefits

	I. Any Receipt of Benefits				II. Amount of Benefits Received			
	Control Mean	ITT	LATE	p-values	Control Mean	ITT	LATE	p-values
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food Stamps (SNAP)	0.599	0.025 (0.0038)	0.095 (0.014)	<.001	1494.346 (1893)	72.75 (15.75)	276.19 (58.85)	<.001
TANF	0.031	0.0031 (0.0015)	0.012 (0.0058)	0.042	111.363 (711)	2.62 (5.94)	9.89 (22.43)	0.659
SSI	0.050	-0.00024 (0.0017)	-0.00092 (0.0065)	0.888	30.626 (137.972)	0.25 (1.08)	0.93 (4.09)	0.821
SSDI	0.084	0.0017 (0.0014)	0.0066 (0.0054)	0.222	943.189 (3401.323)	14.43 (17.33)	54.41 (65.31)	0.405

Note: All outcomes are measured at the individual level except for "Amount of TANF" and "Amount of SNAP" which are the amount that the individual's household received. Columns (1) & (5) report the control mean of the dependant variable and standard deviation for continuous outcomes (in parentheses). Columns (2) and (6) reports coefficient (and standard error in parentheses) on LOTTERY from estimating equation (1) by OLS; columns (3) and (7) reports coefficient (and standard error in parentheses) on MEDICAID from estimating equation (2) by IV. Column (4) reports the p-values. All regressions control for dummies for number of household members on the lottery list and the 2007 value of the dependent variable. Standard errors are clustered by household. All regressions are weighted to adjust for a new lottery that started in late 2009. N=61790.

Welfare Impact?

- Medicaid Lottery increases Food Stamp enrollment
 - What is the welfare impact?
 - Information versus price effects
- Labor supply didn't change -> eligibility didn't change; only enrollment?
 - Was it information?

- GE vs. PE
- Finkelstein (2007)
- Health expenditures are GROWING dramatically
- Could health insurance cause this growth?
- Increases incentive to innovate by creating excess demand
 - Is this bad from a welfare perspective?

- Medicaid is a national program
- Enacted in 1965
- Need variation in intensity of Medicare
 - Card: age 65 discontinuity
 - AER 2008: utilization and mortality - no mortality gain at 65, but low power
 - QJE 2009: mortality in sick population in sample that go to hospital (limits to non-deferrable conditions) – finds mortality improvements
 - Finkelstein: variation in pre-insurance rates
- Conceptually, what's the difference in the strategies?
 - GE vs PE?

Table 1

TABLE I
SHARE OF ELDERLY WITHOUT HOSPITAL INSURANCE, 1963

	Blue Cross	Any insurance
New England (CT, ME, MA, NH, RI, VT)	0.49	0.37
Middle Atlantic (NJ, NY, PA)	0.60	0.41
East North Central, Eastern Part (MI, OH)	0.55	0.32
East North Central, Western Part (IL, IN, WI)	0.75	0.42
West North Central (IA, KS, MN, MO, NE, ND, SD)	0.81	0.47
South Atlantic, Upper Part (DE, DC, MD, VA, WV)	0.75	0.45
South Atlantic, Lower Part (FL, GA, NC, SC)	0.81	0.50
East South Central (AL, KY, MS, TN)	0.88	0.57
West South Central (AR, LA, OK, TX)	0.85	0.55
Mountain (AZ, CO, ID, MT, NV, NM, UT, WY)	0.78	0.50
Pacific (OR, WA, CA, AK, HI)	0.87	0.52
National Total	0.75	0.45

Data are from individuals aged 65 and over in the 1963 National Health Survey. Sample size is 12,757. Minimum sample size for a subregion is 377.

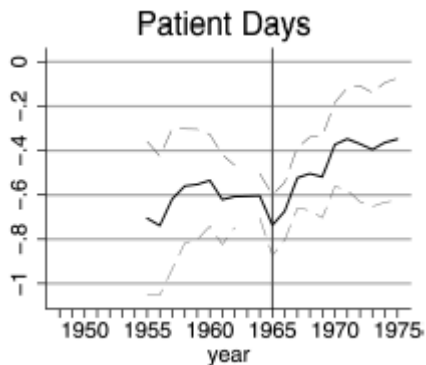
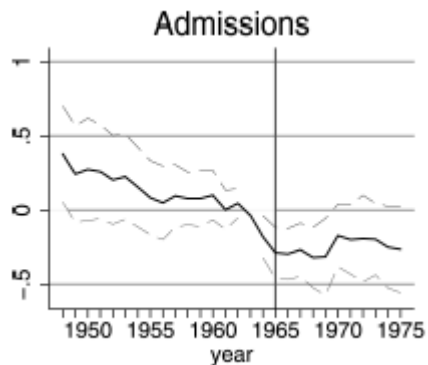
Estimating Equation

$$\log(y_{ijt}) = \alpha_j + \delta_t + \sum_{t=1948}^{1975} \lambda_t Mcareimpact_z * year_t + X_{st}\beta + \epsilon_{ijt}$$

where:

- y_{ijt} is outcome in hospital i in county j at time t
- α_j is county fixed effect
- δ_t is year fixed effect
- X_{st} is outcomes in state s at time t
- $Mcareimpact_z = \%$ elderly in region z without Blue Cross hospital insurance in 1963
- DOES THIS CAPTURE GE EFFECTS? WHY? WHAT COULD BE MISSING?

Results



Results



Results

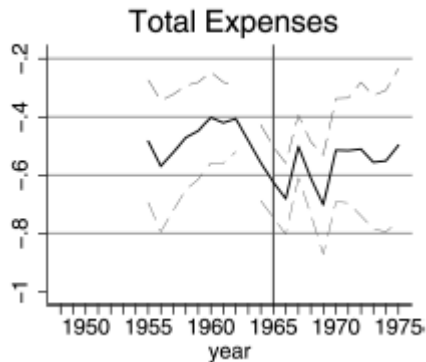


TABLE VI
ANALYSIS OF EXIT AND ENTRY

	Entry analysis (columns 1–2)		Exit analysis (columns 3–4)	
	Unweighted OLS (1)	Weighted OLS (2)	Unweighted OLS (3)	Weighted OLS (4)
$(t - 1965) \times \text{Mcareimpact}$	0.116*** (0.019)	0.121*** (0.017)	0.011 (0.011)	0.013 (0.010)
Mean dep. var. in 1970	0.18	0.18	0.14	0.17

Table reports the coefficient on $(t - 1965) \times \text{Mcareimpact}$ (i.e., β_2) from estimating the OLS deviation-from-trend analysis at the market level (4). For the entry analysis, the dependent variable is the proportion of hospitals in market m in 1960 that have entered between 1960 and year t . For the exit analysis, the dependent variable is the proportion of hospitals in market m in 1960 that have left between 1960 and year t . For all estimates, the sample is limited to 1960 through 1970. All analyses include eight time-varying state-level indicator variables for the number of years before (or since) the implementation of Medicaid in state s . Weighted estimations (in columns 2 and 4) use the number of patient days in a given market in 1960 to weight each market's observations. Standard errors are in parentheses and are calculated allowing for an arbitrary variance-covariance matrix within each hospital market.

***, **, * denotes statistical significance at the 1, 5, and 10 percent levels, respectively. $N = 2,832$.

$$Newtech_{is} = \lambda Mcareimpact_z + X_s \beta + \epsilon_{is}$$

Newtech indicates adoption of technology in hospital i in state s

TABLE VII
 MEDICARE AND THE ADOPTION OF NEW CARDIAC TECHNOLOGIES

	Analysis of open heart surgery (columns 1–5)				Analysis of CICU (columns 6–7)		Difference-in-differences analysis (columns 8–9)		
	<i>Open heart surgery facility</i> (1)	EEG (2)	Postop recovery room (3)	Diagnostic radioactive isotope (4)	Intensive care unit (5)	<i>CICU</i> (6)	Postoperative recovery room (7)	Open heart surgery vs. controls (8)	CICU vs. postoperative recovery room (9)
Without state-level covariates	<i>0.0004</i> (0.065)	-0.182*** (0.059)	-0.087** (0.044)	-0.210*** (0.068)	-0.143*** (0.053)	<i>-0.097</i> (0.095)	-0.341*** (0.106)	0.150*** (0.046)	0.243*** (0.077)
With state-level covariates	<i>0.015</i> (0.063)	-0.087 (0.063)	-0.049 (0.057)	-0.118 (0.072)	-0.054 (0.062)	<i>0.102</i> (0.096)	-0.327** (0.127)	0.123*** (0.048)	0.247*** (0.092)
Year of analysis	1975	1950	1951	1955	1958	1969	1957		
Mean dependent variable	0.09	0.10	0.12	0.10	0.13	0.35	0.35		
Estimating equation	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(7)	(7)

All estimates are marginal effects from probit estimation. Columns (1) through (7) report the marginal effect of *Mcareimpact* from estimation of (6); dependent variable is shown in column heading and results for cardiac technologies are in *italic*. Columns (8) and (9) report the marginal effect of the interaction of *Mcareimpact* with *CARDIAC* indicator from estimation of (7). *CARDIAC* is 1 for the cardiac technology in the analysis, (open heart surgery or CICU) and 0 otherwise. Standard errors (in parentheses) are adjusted for correlation within hospital markets. First row reports results from regressions without covariates. Second row reports results from a separate regression which adds controls for state-level socio-economic characteristics (specifically, real per capita state income, state infant mortality rate, violent crime rate, and state population).

Medicare increases technology adoption
Positive or negative welfare impact?
Transfer?

- 1 The Akerlof Model
- 2 The Screening Model
- 3 Private Information versus Adverse Selection
- 4 Public Health Insurance
- 5 Public/Private Crowd Out**
- 6 Dynamic Insurance

Empirical Literature on Crowd Out: Medicaid

- Cutler and Gruber QJE 1996
- Expansion of Medicaid to pregnant women over 1987-1992
- 50% of increase in coverage associated with reduction in private coverage
- Employees took employer-based coverage less frequently

Empirical Literature on Crowd Out: Medicaid

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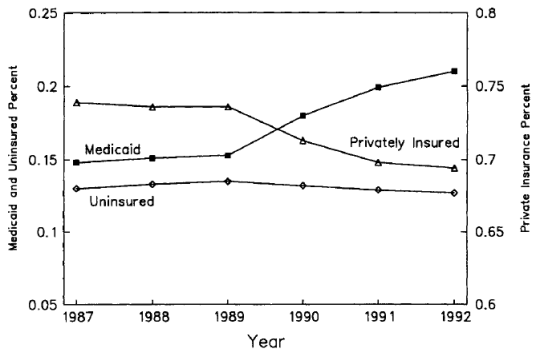


FIGURE IIa
Percent of Children with Different Types of Insurance

PUBLIC INSURANCE AND PRIVATE INSURANCE

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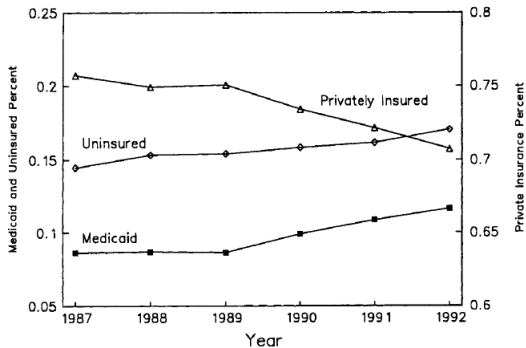


FIGURE IIb
Percent of Women 15-44 with Different Types of Insurance

Empirical Literature on Crowd Out: LTC

- Brown and Finkelstein (AER 2008) use model to calculate impact of Medicaid on LTC demand
- Estimate implicit tax:

$$ImpTax = \frac{\Delta EPDV \text{ of Medicaid Expenditures}}{EPDV \text{ Benefits from LTC policy}}$$

where the numerator is difference in medicaid expenditures with no private insurance vs. with private insurance

- “How much of the LTC policy is captured by Medicaid, not the purchaser”

Implicit Tax

TABLE 2—MEDICAID: IMPLICIT TAX AND COMPLETENESS OF COVERAGE

Wealth percentile	Medicaid share of expected present discounted value (EPDV) of total long-term care expenditures		Implicit tax on private insurance	Net load on private insurance	Willingness to pay for actuarially fair (0 load) policy to top up Medicaid (\$ thousands)
	No private insurance	With private insurance			
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Men</i>					
10th	0.98	0.52	0.998	1.00	0.0
20th	0.89	0.44	0.952	0.98	0.0
30th	0.80	0.41	0.840	0.92	3.3
40th	0.71	0.37	0.737	0.87	9.8
50th	0.60	0.32	0.594	0.80	19.6
60th	0.46	0.26	0.426	0.71	35.2
70th	0.32	0.20	0.272	0.64	51.0
80th	0.17	0.12	0.107	0.55	74.1
90th	0.07	0.05	0.035	0.52	100.9
<i>Panel B: Women</i>					
10th	0.99	0.55	0.999	1.00	0.0
20th	0.93	0.50	0.992	0.99	0.0
30th	0.88	0.46	0.946	0.94	2.3
40th	0.80	0.43	0.854	0.85	11.5
50th	0.72	0.38	0.767	0.75	29.7
60th	0.60	0.33	0.618	0.60	58.3
70th	0.45	0.24	0.470	0.44	86.3
80th	0.24	0.15	0.194	0.15	122.8
90th	0.08	0.06	0.054	0.00	166.3

Notes: Private insurance policy in columns 1–4 has a \$100 daily benefit cap. Implicit tax is the decrease in Medicaid expenditures associated with having private insurance, as a percentage of the private insurance benefits (see equation (5)). Net load is the gross load plus the ratio of the decrease in the EPDV of Medicaid expenditures associated with having private insurance to the EPDV of total long-term care expenditures (equation (6)). Figures are based on the

Why care about crowd-out?

- How was this ruled out in our baseline model?
- What changes with crowd-out?
- Two main theoretical models
 - Chetty and Saez AEJ 2010
 - Golosov and Tvyanski QJE 2007

- 1 The Akerlof Model
- 2 The Screening Model
- 3 Private Information versus Adverse Selection
- 4 Public Health Insurance
- 5 Public/Private Crowd Out
- 6 Dynamic Insurance**

- Reclassification Risk: Basic idea of Hirshleifer 1971
- Realization of information removes the ability to get insurance
- Imposes time-varying participation constraint

Hendel and Lizzeri (QJE 2003)

- Hendel and Lizzeri (QJE 2003) illustrate the role of commitment in life insurance
- Based on Harris and Holmstrom
- Key idea: buyers can't commit to future premium payment
 - Generates front-loading
- Odd feature: symmetric information
- Key problem: doesn't allow private savings (exogenously restricted)
 - What about Arrow-Debreu sequential implementation?

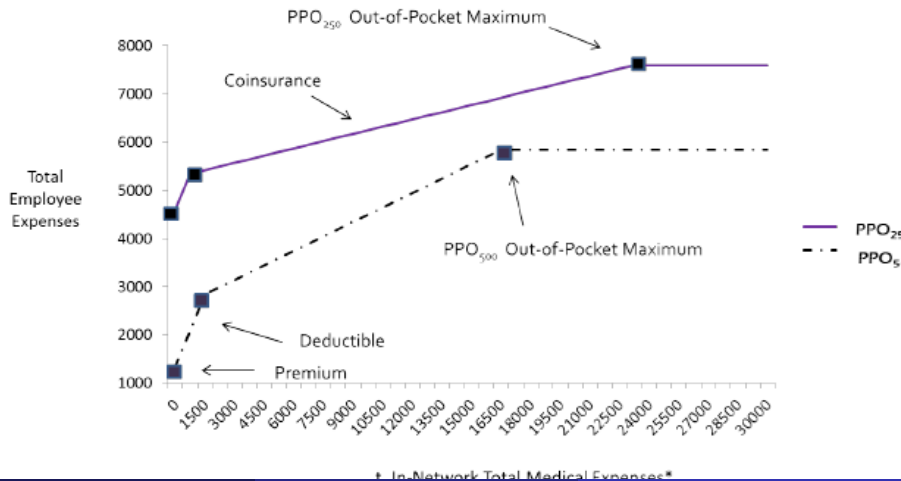
- Optimal disability insurance system
- Involves asset testing
- Prevents “double deviations”

Secondary Markets: Fang and Kung (2010)

- Should people be allowed to re-sell their insurance contracts?
 - “Life settlement” market
- Prevents commitment
- Increases flexibility / choice
- But choice not necessarily welfare improving with asymmetric information

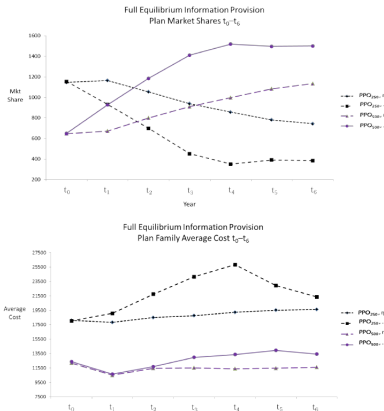
Inertia: Handel (2013)

PPO Health Insurance Plan Characteristics, t_1 Low Income Family



Choice Increases Adverse Selection

FIGURE 3. IMPACT OF REDUCED INERTIA ON CHOICES AND COSTS: WHEN NUDGING HURTS



Note: The top panel of this figure presents the time path of choices for PPO_{250} and PPO_{500} with and without the policy intervention to reduce inertia. With endogenous plan pricing, the impact of the policy intervention on the market share of PPO_{250} relative to PPO_{500} is noticeable. In the benchmark case where there is significant inertia η over the six year period the market share of PPO_{250} declines from 1147 to 744 while that of PPO_{500} increases from 647 to 1134. After the policy intervention reduces inertia to $.25\eta$, PPO_{250} enrollment declines all the way to 385 after six years while PPO_{500} enrollment increases to 1501. In between t_0 and t_6 , there are also noticeable differences in plan enrollment as a result of the policy intervention. The bottom panel in the figure shows the change in average costs for the family coverage tier under the policy intervention relative to the benchmark case of full inertia. The average costs of PPO_{250} increase over time relative to those of PPO_{500} , signaling an increased relative premium for PPO_{250} and increased adverse selection.