Theory: adverse selection can impair efficient operation of insurance markets and create scope for welfare improving government intervention

Raises empirical questions:

- Does selection exist in a particular market?
- What are the efficiency costs of this adverse selection?
- What are the welfare consequences of alternative government interventions?
Testing for selection

Empirical welfare analysis I: Using choices and claims
  - Welfare cost of selection
  - Welfare consequences of government intervention

Empirical welfare analysis II: When can’t use choices
  - Don’t accept revealed preference
  - Markets don’t exist
Outline for Today: testing for selection

Three main topics

- Positive correlation test (Chiapporin and Salanie JPE 2000).
- Issues with positive correlation test:
  - Preference heterogeneity (Finkelstein and McGarry, 2006)
  - Moral hazard
- Cost curve test (Einav, Finkelstein and Cullen 2010)

Overview article: Einav and Finkelstein (JEP 2011)
Adverse selection: downward sloping marginal cost curve

- Demand curve
- AC curve
- MC curve
“Positive correlation” test

- Testing for adverse selection essentially requires testing whether MC curve downward sloping
- Making inferences about marginal individuals can be difficult
- Early empirical approaches developed strategies that could focus on averages
- “Positive correlation” or “bivariate probit” test (Chiappori and Salanie, JPE 2000)
  - “Early” for empirical literature on adverse selection in insurance markets
  - “Late” relative to theory (1970s)!
“Positive correlation” test

- Reject null of symmetric information if there is a positive correlation between insurance coverage and ex-post risk occurrence
- Are average costs of insured higher than average costs of uninsured?
  - At any given price, and in particular at the equilibrium price, adverse selection implies that average cost of insured individuals is higher than average costs of uninsured individuals
“Positive correlation” test: graphical illustration

Using our graphical framework, testing for adverse selection essentially requires us to test whether the MC curve is downward sloping. Making inferences about marginal individuals is difficult, however. As a result, the early empirical approaches developed strategies that attempt to get around this difficulty by, instead, focusing on comparing averages.

The graphical depictions of adverse selection in Figure 1 (or Figure 3) suggest one way to examine whether adverse selection is present in a particular insurance market: compare the expected cost of those with insurance to the expected cost of those without (or compare those with more insurance coverage to those with less coverage).

To see this idea more clearly, consider Figure 5. Here we start with the adverse selection situation already depicted in Figure 3, denoting the AC curve shown in previous figures by $AC_{\text{insured}}$ to reflect the fact that it averages over those individuals with insurance, and adding one more line: the $AC_{\text{uninsured}}$ curve. The $AC_{\text{insured}}$ curve represents the average expected cost of those individuals who do not have insurance. That is, the $AC_{\text{insured}}$ curve is derived by averaging over the expected costs of the insured (averaging “from the left,” starting at $Q = 0$) while the $AC_{\text{uninsured}}$ curve is produced by averaging over the expected costs of the uninsured (averaging “from the right,” starting at $Q = Q_{\text{max}}$). A downward-sloping MC curve implies that...

Note: $AC_{\text{insured}}$ is prior AC curve. $AC_{\text{uninsured}}$ averages over people “from the right”
**Example: Annuitants vs Population Mortality**

<table>
<thead>
<tr>
<th></th>
<th>Annuitant Mortality</th>
<th>Population Mortality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Men</td>
<td>Women</td>
</tr>
<tr>
<td>65</td>
<td>1.02%</td>
<td>0.57%</td>
</tr>
<tr>
<td>75</td>
<td>2.98</td>
<td>1.61</td>
</tr>
<tr>
<td>85</td>
<td>8.06</td>
<td>5.08</td>
</tr>
</tbody>
</table>

“Positive correlation test”: regression version

\[ \text{Coverage}_i = X_i \beta + \varepsilon_i \]
\[ \text{Accident}_i = X_i \gamma + \mu_i \]

- Simultaneously estimate above two equations (e.g. bivariate probit)
  - Under the null of symmetric information, residuals should be uncorrelated
  - Statistically significant positive correlation between two implies rejection of the null hypothesis

- Spawned a cottage industry of papers in many markets (with mixed results)
  - acute health insurance, annuities, life insurance, long term care insurance, Medigap, auto insurance.....
Practical implementation

- Typically implemented by comparing proxies for expected costs across individuals with different insurance coverage
  - Controlling for characteristics that determine prices
  - Crucial to condition on what is priced. Test is among a set of individuals who are treated symmetrically by insurance company!

- Often use data from a single company and examine average claims across individuals who are offered same contracts but who choose more vs. less coverage
Two important limitations to positive correlation test

1. Does not distinguish between adverse selection and moral hazard
2. Not robust to allowing for unobserved preference heterogeneity in addition to unobserved risk type
Moral hazard also generates positive correlation

- Adverse selection: those with private information they are high expected cost self select into insurance market
- Moral hazard: individuals identical before purchasing insurance; those with greater coverage have less incentive to take actions to reduce their expected costs ex post
Moral hazard also generates positive correlation.

A first important limitation of the positive correlation test is that comparing expected costs across individuals with and without insurance may confound adverse selection and moral hazard. Both adverse selection and moral hazard can generate a positive correlation between insurance coverage and claims, but these are two very different forms of asymmetric information with very different implications for public policy. With adverse selection, individuals who have private information that they are at higher risk self-select into the insurance market, generating the positive correlation between insurance coverage and observed claims. As already discussed, the government has several potential welfare-improving policy tools to possibly address such selection. With moral hazard, individuals are identical before they purchase insurance, but have incentives to behave differently after. Those with greater coverage have less incentive to take actions that reduce their expected costs, which will generate a relationship between insurance coverage and observed claims. Unlike in the case of adverse selection, the government typically has no advantage over the private sector at reducing the welfare costs of moral hazard.

Figure 6 shows how moral hazard can produce the same “positive correlation” property as adverse selection produces in Figure 5. Specifically, Figure 6 provides a graphical representation of an insurance market with moral hazard but no selection. The lack of selection is captured by the flat MC curves. Moral hazard is captured by the downward-sloping demand curve.
“Positive correlation” test is joint test of either adverse selection or moral hazard

- Conceptually very different: ex ante vs. ex post private information
- Policy implications different: government tends not to have comparative advantage w moral hazard
  - So really want to know which you have detected
Distinguishing selection from moral hazard

Key point: need exogenous variation in contracts
  - Basic problem: distinguishing treatment (moral hazard) from selection (selection!)

Variety of sources of variation
  - Quasi-Exogenous variation in premiums. e.g.
    - Over time (Cutler and Reber, 1998)
    - Premium RD in income (Finkelstein et al. 2019) or geography (Panhans 2019)
  - Field experiment (e.g. Karlan and Zinman 2009)
Karlan and Zinman (2009)

- Setting: Consumer lender (South Africa)
- Randomized offer interest rate and contract rate on loan
- Selection: compare repayment rate of those offered different rates (but receiving same rate)
- MH: compare repayment rates of those responding to same high offer rate but facing different contract rates

<table>
<thead>
<tr>
<th></th>
<th>High Contract Rate</th>
<th>Low Contract Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Offer Rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Offer Rate</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Moral Hazard

Adverse Selection
Interpreting results of positive correlation test

- Positive correlation may reflect adverse selection, moral hazard, or both
- Lack of positive correlation
  - No asymmetric information
  - Offsetting advantageous selection and moral hazard?
Unobserved heterogeneity in preferences

- Standard theory models: individuals may potentially differ on only one unobserved dimension: risk type
- With unobserved preferences as well, positive correlation between insurance and risk occurrence is not necessary for asymmetric information.
- Example:
  - Private information about risk type and risk aversion
  - More risk averse are lower risk
  - Can get no or negative correlation between insurance and risk occurrence (high risk and low risk but risk averse pool)
  - But there is private information that impairs market efficiency
Recall: Advantageous selection

upward sloping, the AC curve will lie everywhere below it. If there were no insurance loads (as in the textbook situation), advantageous selection would not lead to any inefficiency; the MC and AC curves would always lie below the demand curve, and in equilibrium all individuals in the market would be covered, which would be efficient.

With insurance loads, however, advantageous selection generates the mirror image of the adverse selection case, also leading to inefficiency, but this time due to over-insurance rather than under-insurance. Figure 4 depicts this case. The efficient allocation calls for providing insurance to all individuals whose expected cost is lower than their willingness to pay—that is, all those who are to the left of point $E$ (where the MC curve intersects the demand curve) in Figure 4. Competitive equilibrium, as before, is determined by the intersection of the AC curve and the demand curve (point $C$ in Figure 4). But since the AC curve now lies below the MC curve, equilibrium implies that too many individuals are provided insurance, leading to over-insurance: there are $Q_{eqm} - Q_{eff}$ individuals who are inefficiently provided insurance in equilibrium. These individuals value the insurance at less than their expected costs, but competitive forces make firms reduce the price, thus attracting these individuals together with more profitable infra-marginal individuals. Again, the area of the deadweight loss triangle $EDC$ quantifies the extent of the welfare loss from this over-insurance.

Empirical example: Long-Term Care Insurance

- Finkelstein and McGarry (2006, AER)
- Data from AHEAD cohort of HRS: 1995 - 2000
  - Panel data set on elderly
  - Average age in 1995: 78

Observe in AHEAD:

- In 1995: Do you own long-term care insurance? (11%)
- In 1995: What is your subjective assessment of the chance you go into a nursing home over next five years?
- 1995 – 2000: Do you in fact go into a nh? (16%)
- Detailed demographic and health information

Supplement with:

- External information from insurance companies on what they price on (the X’s you need to condition on in pos corr test)
- Actuarial model of nh use as function of observed demographics and health
Figure 2: Distribution of Subjective Probability of Entering NH within Five Years

Source: 1995 AHEAD Survey
Relationship between LTCI and NH use

We now turn to an examination of what the results from the standard positive correlation test would suggest about asymmetric information in this market. This test also does not distinguish between adverse selection and moral hazard.

B. Long-Term Care Insurance and Long-Term Care Use

The standard test for residual asymmetric information, based on a positive correlation between insurance coverage and risk occurrence conditional on insurance company risk classification, has been applied across a variety of insurance markets with differing results. In the case of health insurance, David Cutler and Richard Zeckhauser (2000) review an extensive literature that tends to find evidence of this positive correlation. The positive correlation also appears in annuity markets (Finkelstein and Poterba, 2002, 2004; McCarthy and Mitchell, 2003). Several papers, however, find no evidence of a positive correlation in life insurance markets (Cawley and Philipson, 1999; McCarthy and Mitchell, 2003) or in automobile insurance markets (Chiappori and Salanie, 2000; Georges Dionne et al., 2001; and Chiappori et al., forthcoming).

Table 3 shows the results of this standard test in the long-term care insurance market. The top row shows the correlation of the residuals from a bivariate probit of long-term care insurance and nursing home use, as in Chiappori and Salanie (2000). The bottom row shows the marginal effect from probit estimation of nursing home use on long-term care insurance (equation (3)), as in Finkelstein and Poterba (2004). Both approaches yield the same findings. With no controls for the insurers’ information set, the relationship between coverage and risk occurrence is negative and statistically significant. This finding is consistent with other aggregate data on relative rates of nursing home use for...

### Table 3—The Relationship Between Long-term Care Insurance and Nursing Home Entry

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

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.
Relationship between LTCI and NH use

To implement this alternative approach, we obtained proprietary data from a large long-term care insurance company which contain all of the information used in similar analyses, including the individual's choice from the menu of contracts, his exact risk classification, and his ex post risk experience. This analysis complements the analysis with the AHEAD data because it allows us to examine the relationship between the quantity of insurance coverage (conditional on having insurance) and risk occurrence. Using these data, we once again fail to reject the null hypothesis of no positive correlation. The data and results from this exercise are described more fully in Appendix B.

We also undertook numerous additional tests of robustness in the AHEAD data, many of which we present in detail in the working paper version (Finkelstein and McGarry, 2003). For example, we verified that the positive correlation does not manifest itself in other measures of care utilization such as the intensity of care use (i.e., number of nights in a nursing home), or home health care use. We also verified that the positive correlation does not emerge if the relationship between insurance coverage and risk occurrence is analyzed over a longer time horizon than the five-year period studied here. Finally, although policies once purchased are guaranteed renewable for life, some individuals stop paying their premiums and thereby forfeit some or all of their potential future nursing home benefits; we therefore verified that the results are unaffected by excluding from the sample the 10 percent of insured individuals in 1995 who subsequently report having dropped their insurance coverage.

The results presented in Tables 1 and 2 point to the presence of asymmetric information, even though the results in Tables 3 and 4 indicate that the standard positive correlation test is unable to reject the null of symmetric information. This suggests that our beliefs-based test may be a more discerning test for asymmetric information than the standard positive correlation test. Moreover, as noted previously, because our beliefs measure is a highly imperfect proxy for an individual's private information, our findings in Tables 1 and 2 likely understate the amount of private information in this market.

Nonetheless, a natural question is whether the private information we detected in Tables 1 and 2 is sufficiently large that we should have ex-

<table>
<thead>
<tr>
<th>Table 4—Relationship between LTCINS and CARE</th>
</tr>
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<tbody>
<tr>
<td>(Sample restricted to individuals with same choice set)</td>
</tr>
</tbody>
</table>

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

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.
But individuals have residual private information

Table 2 reports the results from estimating the relationship between beliefs and insurance coverage in equation (2). The results indicate that individuals who believe that they are of higher risk are also more likely to have insurance. By contrast, the insurance company’s prediction of the individual’s risk is negatively related to insurance coverage; this is consistent with the results below that, in fact, on average risk type and insurance coverage are negatively correlated. It also supports our use of the insurance company prediction as a proxy for insurance pricing; conditional on the individual’s risk assessment, a higher insurance company prediction implies a higher price relative to the individual’s perception of an actuarially fair price, and therefore reduces the probability of purchase.

Taken together, the results in Tables 1 and 2 indicate that individuals have residual private information that predicts their risk type and is positively correlated with insurance ownership. This provides direct evidence of asymmetric information. It does not, however, allow us to distinguish between ex ante private information (adverse selection) and ex post private information (moral hazard). Other empirical evidence suggests that demand for nursing home use is relatively price inelastic (David Grabowski and

<table>
<thead>
<tr>
<th>Table 1—Relationship between Individual Beliefs and Subsequent Nursing Home Use</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Individual prediction</td>
</tr>
<tr>
<td>Insurance company prediction</td>
</tr>
<tr>
<td>pseudo-$R^2$</td>
</tr>
<tr>
<td>$N$</td>
</tr>
</tbody>
</table>

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.
And private information positively correlated with LTCI.

Table 2 reports the results from estimating the relationship between beliefs and insurance coverage in equation (2). The results indicate that individuals who believe that they are of higher risk are also more likely to have insurance. By contrast, the insurance company's prediction of the individual's risk is negatively related to insurance coverage; this is consistent with the results below that, in fact, on average risk type and insurance coverage are negatively correlated. It also supports our use of the insurance company prediction as a proxy for insurance pricing; conditional on the individual's risk assessment, a higher insurance company prediction implies a higher price relative to the individual's perception of an actuarially fair price, and therefore reduces the probability of purchase.

Taken together, the results in Tables 1 and 2 indicate that individuals have residual private information that predicts their risk type and is positively correlated with insurance ownership. This provides direct evidence of asymmetric information. It does not, however, allow us to distinguish between ex ante private information (adverse selection) and ex post private information (moral hazard). Other empirical evidence suggests that demand for nursing home use is relatively price inelastic.

### Table 2—Relationship between Individual Beliefs and Insurance Coverage

<table>
<thead>
<tr>
<th></th>
<th>No controls</th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.086***</td>
<td>0.099***</td>
<td>0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.017)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Insurance company prediction</td>
<td>-0.125***</td>
<td>-0.140***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
<td></td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>0.007</td>
<td>0.010</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>5,072</td>
<td>5,072</td>
<td>5,072</td>
</tr>
<tr>
<td>$N$</td>
<td></td>
<td></td>
<td>4,780</td>
</tr>
</tbody>
</table>

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.
On average, those who own long term care insurance are not more likely to subsequently go into nursing home.

- In preferred specification they are less likely to go into nursing home.

Therefore application of positive correlation test leaves us unable to reject null of symmetric information.

But direct evidence of private information about risk type:

- Conditional on insurance company information, individuals’ subjective beliefs about expected nh use predict subsequent utilization.

Moreover, residual private information positively correlated with long term care insurance coverage.
Potential reconciliation

- Individuals have private information about their risk type that is positively correlated with insurance coverage (and nh use)
  - Yet insured individuals not more likely to enter a nursing home than uninsured individuals

- Possible reconciliation: other unobserved characteristics of the individual are positively correlated with insurance coverage but negatively correlated with insurance use
  - NB: these must be characteristics that are not priced

Finkelstein ()
Evidence of preference based selection

Table 5—Preference-Based Selection

<table>
<thead>
<tr>
<th>Panel A: Wealth</th>
<th>No controls</th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NH Entry</td>
<td>LTC Insurance</td>
<td>NH Entry</td>
</tr>
<tr>
<td>Top wealth quartile</td>
<td>−0.095*** (0.013)</td>
<td>0.150*** (0.020)</td>
<td>−0.038** (0.014)</td>
</tr>
<tr>
<td>Wealth quartile 2</td>
<td>−0.073*** (0.013)</td>
<td>0.104*** (0.020)</td>
<td>−0.025* (0.014)</td>
</tr>
<tr>
<td>Wealth quartile 3</td>
<td>−0.030** (0.015)</td>
<td>0.062*** (0.020)</td>
<td>0.0004 (0.016)</td>
</tr>
<tr>
<td>Bottom wealth quartile (omitted)</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.086*** (0.021)</td>
<td>0.089*** (0.017)</td>
<td>0.042** (0.020)</td>
</tr>
</tbody>
</table>

Panel B: Preventive health activity

<table>
<thead>
<tr>
<th>Preventive activity</th>
<th>No controls</th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NH Entry</td>
<td>LTC Insurance</td>
<td>NH Entry</td>
</tr>
<tr>
<td>Preventive activity</td>
<td>−0.106*** (0.0118)</td>
<td>0.066*** (0.017)</td>
<td>−0.054*** (0.018)</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.095*** (0.021)</td>
<td>0.082*** (0.017)</td>
<td>0.047** (0.020)</td>
</tr>
</tbody>
</table>

Panel C: Seat belt use

<table>
<thead>
<tr>
<th>Always wear seatbelt</th>
<th>No controls</th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NH Entry</td>
<td>LTC Insurance</td>
<td>NH Entry</td>
</tr>
<tr>
<td>Always wear seatbelt</td>
<td>−0.059*** (0.014)</td>
<td>0.053*** (0.010)</td>
<td>−0.031** (0.013)</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.092*** (0.021)</td>
<td>0.084*** (0.017)</td>
<td>0.044** (0.020)</td>
</tr>
</tbody>
</table>
Perspective on the-paper-as-a-paper

- **Strengths:**
  - documents an important limitation with an existing literature
  - opens up new areas of research

- **Empirical Weaknesses:**
  - Subjective probabilities are ordinal not cardinal
  - Don’t observe option set for each person (have to crudely proxy)
    - not ideal for testing
  - Shows limitation of positive correlation test without proposing an alternative

- **Conceptual Weaknesses**
  - What is the underlying primitive of the preference heterogeneity
  - What are the implications for welfare??
Implications for testing

- Asymmetric information can exist even when there is no positive correlation between insurance coverage and risk occurrence
  - i.e. positive correlation test not robust to preference heterogeneity
- Motivates “Unused observables” test for asymmetric information (Finkelstein and Poterba 2014)
  - Reject null of symmetric information if, conditional on information of insurance company, econometrician can observe a characteristic of the individuals that is correlated (in any direction) with both quantity of insurance coverage and ex post risk occurrence
  - Downside: one sided (and conflates selection and moral hazard)
  - Application: UK annuity market; geographic location. Why unused?
Implications for welfare

- Advantageous selection
  - Upward sloping MC curve
  - Too much insurance

- What if marginal cost curve is flat?
  - E.g. If interpret Finkelstein and McGarry (2006) to be “no correlation” (pretty knife edge)
  - Then equilibrium is constrained efficient (if price is only instrument) but not first best

- NB: once have preference heterogeneity, positive correlation indicates private information (and inefficiency) but lack of pos correlation does not rule out either.
Preference heterogeneity is empirically important.

- **Long term care insurance**
  - Advantageous selection on risk aversion (F&M, AER 2006)

- **Medigap insurance**
  - Advantageous selection on cognitive ability (Fang, Keane and Silverman (JPE 2008)). Those with Medigap have lower medical expenditures and higher cognitive ability.

- **Automobile insurance** (Cohen and Einav 2007)
  - Evidence that heterogeneity in unobserved risk aversion larger than heterogeneity in unobserved risk type.
  - Find risk aversion and risk type positively correlated.
  - Preferences can reinforce adverse selection.
Passive vs. Active Selection: Does it Matter?

- Life insurance vs annuities
- Annuities: Payments as long as you survive
- Life insurance: Payments when you die
- Insure opposite risks.
- Evidence of adverse selection in annuities but not life insurance
- Potential explanation: Perhaps higher risk aversion (or higher wealth) people both demand more insurance and are longer lived
  - Passive Selection vs Active Selection
Preference heterog. theoretically difficult

- Multiple dimensions of private information substantially complicated theory
- Fixing contract space (in the graphs) made life a lot easier!
- Many insurance models endogenize contract space (e.g. R&S 1976) but have uni-dimensional heterogeneity
  - with multi-dimensional heterogeneity no longer have single crossing
- Azevedo and Gottlieb (EMA 2017) endogenize contract space with multiple dimensions of heterogeneity
  - Maintain perfect competition assumption
Addressing the limitations of the positive correlation test

Recall two key issues:
- Not robust to preference heterogeneity
- Joint test of moral hazard and selection

“Cost curve” test of selection (Einav, Finkelstein and Cullen, 2010)
- Addresses both these issues
- But higher data hurdle (need quasi-random variation in prices)
Cost curve test (Einav, Finkelstein and Cullen 2010)

- Idea: slope of MC curve provides a direct test of existence and nature of selection
- Reject null of no selection if reject null of constant MC curve
- Slope of cost curve indicates if selection is adverse or advantageous
Cost curve test implementation

- Estimate average cost curve on sample who are insured

\[ c_i = \gamma + \delta p_i + u_i \]

- Estimating how costs change for endogenously selected sample of those who stay insured as you vary the price
  - = key idea of selection.

- Data requirements higher than for positive correlation test:
  - As with positive correlation test, need to know insurance coverage (since limit sample based on this) and costs (left hand side)
  - Additional data hurdle: Also need exogenous variation in prices
Aside: Selecting on the endogenous outcome

- Useful if you want to understand the *characteristics* of those who respond to the intervention

- Other examples:
  - What type of DI applicants deterred from hassles (Deshpande and Li forthcoming)?
  - Who is the marginal child when abortion is legalized (Gruber, Levine and Staiger 1999)?

- More generally: "characterizing the compliers" (Abadie 2002).
Cost curve test: example from Colorado health insurance exchange

- Panhans (2019 AEJ: Applied)
- Colorado Health Insurance Exchange 2014
  - Created by Affordable Care Act (ACA)
  - Subsidized for low income individuals
- Statewide data on premiums, claims, insurance coverage (exchange coverage vs. not)
- Source of premium variation: geographic discontinuities in insurance premiums at boundaries of "rating areas" established by law
  - Premiums change discretely at "artificial" boundaries of rating areas
  - Compare costs of those enrolled on either side of the border (fixed effect for each zip code pair $\phi_g(k)$)

$$c_i = \gamma + \delta p_{ik} + \phi_g(k) + u_i$$
A. Boundary Discontinuity

The designation of rating areas in Colorado for 2014 is shown in Figure 2 at the zip code level. Individuals living in zip codes along the rating area boundary, despite living only a short distance away from each other and facing the same health care provider markets, can face potentially very different premiums. To exploit this discontinuity, for each zip code on a rating area boundary, all of the neighboring zip codes that were in a different rating area were identified. Zip codes were then paired with a neighboring zip code if one met the following criteria: was in a different rating area, but the same local medical market, and the two zip codes mutually shared the longest border with each other.

In the main specifications, I use hospital referral regions (HRRs) as the definition of the medical market. This definition comes from the Dartmouth Atlas, and Figure 2 shows a map of the zip codes in Colorado assigned to HRRs. With this definition, the zip code pairing algorithm yields 32 pairs of zip codes. For robustness, I also consider other market definitions, such as hospital service areas (HSAs), which are depicted in online Appendix Figure A1. Because HSAs are smaller areas, this leaves fewer candidate zip codes for the boundary, as made clear through the figure.

Within each pair, individuals who resided across the boundary would face different premiums because of the way the community rating was designed. However, the difference varies across matched zip codes. Figure 3 shows the difference in monthly premium that a 30-year-old nonsmoker would face for a standard silver plan from HMO Colorado (Blue Cross Blue Shield).

Figure 2. 2014 Rating Areas in Colorado

Notes: Five-digit zip codes are shown grouped into rating areas based on color. The outlines designate the grouping of zip codes into medical markets, here defined as the Hospital Referral Region (HRR).
Beginning in 2014, as a consequence of the community rating provisions of the ACA, insurers submit rate tables with age and area factors that will determine an individual's monthly premium. These factors are multiplied by a plan's base rate to determine the final premium. For example, a standard silver plan from HMO Colorado has a base rate of $262.13 as the monthly premium. The monthly premium an individual $i$ residing in zip code $k$ would have to pay for the plan depends on the insurer's area factor $\text{ARE}_k$ and age factor $\text{AGE}_i$, by the following formula:

$$\text{pre}_i^k = 262.13 \times \text{ARE}_k \times \text{AGE}_i.$$
Cost curve indicates selection.

The results shown in online Appendix Table A9 imply that a 1 percent increase in the insurance premiums in an area increases the annual medical expenditures of the insured population by about 0.8 percent, and the corresponding placebo regressions in online Appendix Table A10 bolster the validity of the research design.

There is also heterogeneity in the acuteness of selection across different age segments of the market. Differences in take-up rates suggest this may be the case, with 60 percent of 55–64 year olds purchasing insurance, and only 36 percent of 25–34 year olds. To detect differences in acuteness of selection across age groups, I interact the premium increase with age. For this specification, I group the sample into four age bins: 27–34, 35–44, 45–54, and 55–64, and interact each age bin indicator with the premium level. The results using the premium of the average silver plan are shown in Table 5, and indicate that selection is most acute at the older end of the age distribution.

As an alternative, the age heterogeneity can be estimated using log costs and the percent increase in premiums. With this specification, however, a different story emerges, with the middle-age groups appearing to account for most of the selection, and particularly individuals in the 35–44 age range. I estimate this specification using a median regression, as it is more robust to outliers, and allow the coefficient of interest to interact with a polynomial of the individual's age. The regression results are shown in online Appendix Table A11 with a quadratic term.

\[ \log \left( 1 + c_i \right) = \gamma + \delta \left( \text{pre}_{mk} - \text{pre}_{mk} \text{L} \right) + \phi g(k) + \mu_i, \]

where \( \text{pre}_{mk} \text{L} \) is the premium faced by that individual when residing in the less expensive side of the zip code pair. In this formulation, the term on the \( \delta \) coefficient equals zero for individuals in the less expensive zip code. A more standard way to run this regression would be to simply include the log premium for each \( i \) in the regression. However, because log differences approximate percent changes best for small percent changes, and the percent increases across some of the boundaries are >20 percent, and up to a 50 percent increase, the interpretation of the log specification deviates compared to using the mathematical definition of the percent change.

**Figure 5. Binned Scatterplot of Selection Regression**

*Notes:*
Panel A presents graphically the results from the placebo regression in column 1 of Table 4. Panel B presents the results from the main OLS results in panel A, column 1 of Table 3, which indicate adverse selection. The sample means of premiums have been added back in to the premium residuals before plotting.
Cost curve test: example from MA health insurance exchange

- Finkelstein et al. (2019)
- Subsidized health insurance exchanged introduce in MA in 2006 ("Romneycare")
  - Precursor to ACA exchanges
- Data on premiums, claims, enrollment
- Source of premium variation: regression discontinuity in premium subsidies by income
  - Public subsidies designed to make insurance "affordable"
  - Increase at discrete income bins
Quasi-random Variation in Premiums

Panel A: Premiums for Cheapest Plan (2009-2013)

NOTE: Panel A plots enrollee premiums for the cheapest plan by income as a percent of FPL, noting the thresholds (150%, 200%, and 250% of FPL) where the amount increases discretely. The black lines show the values that applied in 2009-2012; the gray lines show the (slightly higher) values for 2013. Panel B shows insurer prices (dotted lines) and enrollee premiums (solid lines) for the five plans in 2011. In this year, four insurers set prices within $3 of a $426/month price cap, while CeltiCare set a lower price ($405) and therefore had lower enrollee premiums.

2011 Plan Options
We analyze the market in 2009-2013 but focus especially on fiscal year 2011 when the market had a useful vertical structure with plans falling into two groups. In 2011 CommCare imposed a binding cap on insurer prices of $426 per month. Four insurers – BMC HealthNet, Fallon, Neighborhood Health Plan, and Network Health – all set prices within $3 of this cap. The exception was CeltiCare, which set a price of $405 per month. Figure 1, Panel B shows these insurer prices and the resulting post-subsidy enrollee premiums by income. The prices and premiums of the four high-price plans are nearly indistinguishable, while CeltiCare's premium is noticeably lower.

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Demand and cost as function of premiums

Figure 4: CommCare Enrollment and Average Insurer Costs, 2009-2013

Panel A: Average Monthly Enrollment by Income

RD = -1735 (131)
%Δ = -37%

RD = -869 (89)
%Δ = -34%

RD = -437 (89)
%Δ = -31%

Panel B: Average Monthly Insurer Costs

RD = 47.3 (7.7)
%Δ = +15%

RD = 32.4 (8.7)
%Δ = +9%

RD = 6.2 (11.9)
%Δ = +2%

NOTE: The figure shows discontinuities in enrollment and average insurer costs at the income thresholds (150%, 200%, and 250% of FPL) at which enrollee premiums increase (see Figure 1). Panel A shows average enrollment in CommCare (total member-months, divided by number of months) by income over the 2009-2013 period our data spans. Panel B shows average insurer medical costs per month across all CommCare plans over the same period. In each figure, the dots represent raw values for a 5% of FPL bin, and the lines are predicted lines from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled just to the right of each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “% Δ =”. 

Figure 5: CommCare Enrollment, 2011

Panel A: Any Plan

RD = -1054 (318)
%Δ = -26%

RD = -641 (157)
%Δ = -27%

RD = -326 (99)
%Δ = -25%

Panel B: HP l a n

RD = -715 (270)
%Δ = -21%

RD = -642 (141)
%Δ = -30%

RD = -293 (88)
%Δ = -25%

NOTE: Figure shows average enrollment (defined as total member-months, divided by number of months) by income in 2011. Panel A shows enrollment in any CommCare plan, Panel B shows enrollment in the HP l a n plan. In each figure, the dots represent raw averages for a 5% of FPL bin, and the lines (and labels) are predicted lines from our linear RD specification in equation (1). RD estimates and robust standard errors (in parentheses) are labeled just to the right of each discontinuity; percent changes relative to the value just below the discontinuity are labeled as “% Δ =”.

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HEALTH INSURANCE SUBSIDIES: WHAT DO THEY DO AND WHAT DOES THAT MEAN?

Constructing demand curve

Observed Demand Points

Share with Formal Insurance

$/month

150% FPL
200% FPL
250% FPL

(0.94, $0)
(0.70, $39)
(0.76, $39)
(0.56, $77)
(0.58, $77)
(0.44, $116)

0 25 50 75 100 125

0 25 50 75

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Cost curve test comments

- Can detect adverse or advantageous selection (slope of cost curve)
- “Cost curve” test not affected by existence (or lack thereof) of moral hazard
  - Estimate cost curve on sample in which coverage is fixed
  - Of course slope of cost curve may reflect selection based on differential expected responsiveness to incentive effects
    - “Selection on moral hazard” (Einav, Finkelstein, Ryan, Schrimpf and Cullen 2013)
Complementarities between theory and empirics

- Original seminal theory assumed single dimensional heterogeneity
- Empiricals work suggests multiple dimensions of heterogeneity
  - Complicating both theory and empirics
- Both responding and evolving
  - Empirical work advanced by fixing contract space
  - Recent theory (Azevedo and Gottlieb EMA 2017) endogenizes contract space with multiple dimensions of heterogeneity (and perfect competition)
    - Takes it to the data
- Next steps?
Other consequences of adverse selection

- Most existing work looks at impact of adverse selection on (mis-) pricing and insurance coverage
- Selection may also give insurers incentives to distort plan benefits (Rothschild-Stiglitz 1976)
- Very little existing work (using EFC test or otherwise) looking at impact of selection on contract / benefit design
  - Formulary (drug benefit) design to discourage high cost enrollees (e.g. high cost-sharing for HIV drugs in health insurance exchanges - Jacobs and Sommers 2015 NEJM perspective)
  - Shepard (2016 JMP): Broader networks attract higher cost enrollees
Massachusetts pioneer health insurance exchange for low income individuals (Commcare)

In 2012, one plan (Network Health Plan) substantially limits its network of providers
  - drops Partners ("star hospitals" - MGH, BWH)
Figure 3. Plan Switching and Selection when Network Health Drops Partners in 2012

NOTE: These figures show switching and selection patterns for Network Health enrollees around its 2012 dropping of Partners and several other hospitals. The top graph shows the share of Network Health's enrollees who switch out of the plan at each year's open enrollment – separately for past Partners patients (in blue), past patients of other dropped hospitals (in red), all other enrollees (in green), and the average for all enrollees (black dashed line). Past patients of Partners and other dropped hospitals are much more likely to switch away from the plan in 2012 than other years. The bottom graph shows the average cost (during the prior year) of stayers, switchers out of, and switchers into Network Health at each year's open enrollment. In 2012, the cost of switchers out of Network Health was sharply higher, driven by the exit of past Partners patients. These results also hold for risk-adjusted costs (see Appendix Table 4 for additional details on the cost of stayers and switchers).
High cost enrollees switch out of limited network plan

Figure 3. Plan Switching and Selection when Network Health Drops Partners in 2012

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Implications

- (Rare) evidence of how selection may affect benefit design
  - Broader networks attract higher cost enrollees
- Interestingly, note that this adverse selection of broad network plans occurs despite "state of the art" risk adjustment
  - To counteract adverse selection, plans are reimbursed more for patients who are predicted to be higher cost on the basis of their "risk score" - predictive model of spending based on demographics and past diagnoses
- Why might risk scoring be inadequate?
  - Statistical prediction challenge
    - Need better data, more sophisticated algorithms
  - Economic / conceptual challenge:
    - selection may not just be on levels (expected health costs) but also on slope (responsiveness of behavior to plan)
    - selection on moral hazard (Roy model)
Testing for asymmetric information: Important questions remain

- Examining consequences of adverse selection for benefit design (a la Shepard)
- Many markets have not been studied at all (e.g. adverse selection in Disability Insurance if offered a choice?)
  - There's lots of public policy (and research on the public policy) but not on the underlying market failure
- Why don't insurance companies price on more observable characteristics?
Recent Evidence of Adverse Selection in Unemployment Insurance

- Landais, Nekoei, Nilsson, Seim and Spinnewijn (2017 WP) "Risk-based selection in UI: evidence and implications"
- Study demand for (optional, public) supplemental UI in Sweden
  - Swedish workers entitled to minimum benefit financed by payroll tax
  - Option to buy a more comprehensive policy (same duration etc, just higher payouts) at a (uniform) premium set by government
- Administrative data on worker choices and outcomes
- Implement the whole panoply of tests and discuss what learn from each
  - positive correlation test
  - unused observables test
  - cost curve test
- Provides nice review / test your understanding of lecture material
  - The last section of the paper builds on the welfare analysis we are going to discuss next...