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

Price

Demand curve

MC curve

AC curve

$P_{eqm}$

$P_{eff}$

$Q_{eqm}$

$Q_{eff}$

$Q_{max}$

May not be efficient to insure all
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{\textsubscript{insured}} to reflect the fact that it averages over those individuals with insurance, and adding one more line: the AC\text{\textsubscript{uninsured}} curve. The AC\text{\textsubscript{uninsured}} curve represents the average expected cost of those individuals who do not have insurance. That is, the AC\text{\textsubscript{insured}} curve is derived by averaging "from the left," starting at \(Q = 0\) while the AC\text{\textsubscript{uninsured}} curve is produced by averaging over the expected costs of the uninsured (averaging "from the right," starting at \(Q = Q\text{\textsubscript{max}}\)). A downward-sloping MC curve implies that...

Note: AC\_insured is prior AC curve. AC\_uninsured averages over people “from the right”
### Example: Annuitants vs Population Mortality

<table>
<thead>
<tr>
<th>Age</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.....
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 that 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.
“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 (e.g. Cutler and Reber, 1998)
  - Premium RD in income (e.g. Finkelstein et al. 2019) or geography (e.g. 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>N/A</td>
<td></td>
</tr>
</tbody>
</table>

- Moral Hazard
- Adverse Selection

Finkelstein ()
PF Slides  Fall 2020
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
Overview

- Positive correlation test unable to reject null of symmetric information
  - On average, those who own long term care insurance are not more likely (indeed less likely) to subsequently go into nursing home
- But direct evidence that individuals have private information about their risk type that is positively correlated with both insurance coverage and subsequent nursing home use:
  - Conditional on insurance company information, individuals’ subjective beliefs about expected nh use correlated with insurance coverage AND predict subsequent utilization
- 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
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>
<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>−0.105***</td>
<td>−0.047</td>
<td>−0.028</td>
</tr>
<tr>
<td>(p = 0.006)</td>
<td></td>
<td>(p = 0.25)</td>
<td>(p = 0.51)</td>
</tr>
<tr>
<td>Coefficient from probit of CARE on LTCINS</td>
<td>−0.046***</td>
<td>−0.021</td>
<td>−0.014</td>
</tr>
<tr>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td></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-reject the null hypothesis of no positive correlation. The data and results from this exercise are described more fully in Appendix B.

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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 4—Relationship between LTCINS and CARE

<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 [945VOL. 96 NO. 4 FINKELSTEIN AND MCGARRY: MULTIPLE DIMENSIONS OF PRIVATE INFORMATION]

### Table 1—Relationship between Individual Beliefs and Subsequent Nursing Home Use

<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>0.091***</td>
<td>0.043**</td>
<td>0.037*</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Insurance company prediction</td>
<td>0.400***</td>
<td>0.395***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
<td></td>
</tr>
<tr>
<td>pseudo-$R^2$</td>
<td>0.005</td>
<td>0.097</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>N</td>
<td>5,072</td>
<td>5,072</td>
<td>5,072</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4,780</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 (David Grabowski and

Table 2—Relationship between Individual Beliefs and Insurance Coverage

<table>
<thead>
<tr>
<th></th>
<th>No controls (1)</th>
<th>Control for insurance company prediction (2)</th>
<th>Control for application information (3)</th>
</tr>
</thead>
<tbody>
<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></td>
<td>−0.125***</td>
<td>−0.140***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.023)</td>
<td>(0.023)</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></td>
<td></td>
<td>4,780</td>
<td></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.
Evidence of preference based selection

tivity affects the mean as well as the variance of the risk distribution (see, e.g., Dionne and Eeckhoudt, 1985, and Jullien et al., 1999). Thus the sign of the correlation between cau-
tious behavior and insurance coverage is an empirical question. The results in Table 5, panel B, indicate that individuals who un-
dertake a greater fraction of potential preven-
tive health activities (i.e., more cautious individuals) are in fact more likely to own insurance; they are also less likely to enter a
nursing home.24

One interpretation of the negative relation-
ship between preventive health behaviors and
nursing home use is that the preventive behav-
iors endogenously lower the individual's risk type by forestalling or preventing nursing home
admissions. For example, flu shots reduce the risk of pneumonia which is a nontrivial contrib-
utor to nursing home use among the elderly. We
also find, however, that individuals who invest
more in our measured preventive health activi-
ties are substantially less likely to have a hip
fracture (another important contributor to nurs-
ing home use), yet none of the measured activ-
ities themselves would be expected to affect
bone density or agility. We therefore suspect
that these preventive health activities are corre-
lated with other health investments that them-
selves cause lower rates of institutionalization.
It is also possible that these preventive health
activities proxy for other unmeasured preference-
related characteristics that themselves have a
causal effect on nursing home utilization. We
find, for example, that individuals who engage
24 We verified that these results are robust instead to mea-
suring preventive health activity subsequent to the in-
surance contracting in 1995 (i.e., over the period 1998 –
2000).

### Table 5—Reference-Based Selection

<table>
<thead>
<tr>
<th></th>
<th>No controls</th>
<th></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>
<td>LTC Insurance</td>
</tr>
<tr>
<td>Panel A: Wealth</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top wealth quartile</td>
<td>−0.095***</td>
<td>0.150***</td>
<td>−0.038**</td>
<td>0.131***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Wealth quartile 2</td>
<td>−0.073***</td>
<td>0.104***</td>
<td>−0.025*</td>
<td>0.089***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Wealth quartile 3</td>
<td>−0.030**</td>
<td>0.062***</td>
<td>0.0004</td>
<td>0.052***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.020)</td>
<td>(0.016)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Bottom wealth quartile (omitted)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.086***</td>
<td>0.089***</td>
<td>0.042**</td>
<td>0.098***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.017)</td>
</tr>
</tbody>
</table>

Panel B: Preventive health activity

<table>
<thead>
<tr>
<th></th>
<th>No controls</th>
<th></th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preventive activity</td>
<td>−0.106***</td>
<td>0.066***</td>
<td>−0.054***</td>
<td>0.052***</td>
</tr>
<tr>
<td></td>
<td>(0.0118)</td>
<td>(0.017)</td>
<td>(0.018)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.095***</td>
<td>0.082***</td>
<td>0.047**</td>
<td>0.095***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.017)</td>
</tr>
</tbody>
</table>

Panel C: Seat belt use

<table>
<thead>
<tr>
<th></th>
<th>No controls</th>
<th></th>
<th>Control for insurance company prediction</th>
<th>Control for application information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Always wear seatbelt</td>
<td>−0.059***</td>
<td>0.053***</td>
<td>−0.031**</td>
<td>0.048***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.010)</td>
<td>(0.013)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Individual prediction</td>
<td>0.092***</td>
<td>0.084***</td>
<td>0.044**</td>
<td>0.097***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.017)</td>
</tr>
</tbody>
</table>
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??
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 theory

- Multiple dimensions of private information substantially complicates theory
- 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
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 no free lunch: now 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

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

- \( c_i \) is average insurable costs (claims)
- \( p_i \) is price of insurance

- 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 empirical 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 AI. 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).

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).
amounts to around a 1 percent increase in monthly premiums, while in others it can mean an increase of over 40 percent. The median difference is a 15 percent increase in monthly premiums across the boundary.

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 $\text{AG}_E$, by the following formula:

$$\text{pre}_{imk} = 262.13 \times \text{ARE}_k \times \text{AG}_E.$$

Denote by $g(k)$ the group to which zip code $k$ has been assigned, and $c_i$ the annual medical spending of individual $i$ in 2014. Then the estimating equation to detect adverse selection is

$$c_i = \gamma + \delta \cdot \text{pre}_{imk} + \phi g(k) + \mu_i,$$

where $\text{pre}_{imk}$ is the premium that individual $i$ residing in zip code $k$ faces for insurance. The $\phi g(k)$ denotes a fixed effect for each group of zip codes that have been matched, such that the identifying variation comes only from individuals within matched zip codes. Because matched zip codes are required to be in the same local

---

**Figure 3. Change in Premium across Rating Area Boundary**

*Notes:* There are 32 pairs of neighboring zip codes that cross a rating area while remaining in the same HRR. This graph shows the change in monthly premium for Blue Cross Blue Shield’s Silver Plan across each of the 32 pairs of zip codes.
Cost curve indicates selection

Panel A. 2013: Placebo regression
Panel B. 2014: Adverse selection

**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)

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This target amount was set separately for several bins of income, with discrete changes at 150%, 200%, and 250% of FPL. Figure 1, Panel A shows the result: enrollee premiums for the cheapest plan vary discretely at these thresholds. For the years 2009-2012 (shown in black), the cheapest plan is free for individuals below 150% of FPL and increases to $39 per month above 150% FPL, $77 per month above 200% FPL, and $116 per month above 250% of FPL. In 2013 (shown in gray), these amounts increase slightly to $0 / $40 / $78 / $118. Consistent with the goal of affordability, these premiums were a small share of income. For instance, for a single individual in 2011 (whose FPL equaled $908 per month), these premiums ranged from 0-5% of income (specifically, 2.9% of income just above 150% FPL, 4.2% just above 200% FPL, and 5.1% just above 250% FPL).

Figure 1: Insurer Prices and Enrollee Premiums in CommCare Market
Panel A: Premiums for Cheapest Plan (2009-2013)
Panel B: Prices, Subsidies, and Premiums in 2011

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.
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%
Constructing demand curve

Observed Demand Points

- 150% FPL: (0.94, $0)
- 200% FPL: (0.70, $39), (0.76, $39), (0.56, $77), (0.58, $77), (0.44, $116)
- 250% FPL: (0.44, $116)

Share with Formal Insurance

$/month

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

Observed Average Costs

Average Cost

Share with Formal Insurance

FPL Levels:
- 150% FPL
- 200% FPL
- 250% FPL
Moral hazard and the cost curve test

- “Cost curve” test not affected by existence (or lack thereof) of moral hazard
  - Estimate cost curve on sample in which coverage is fixed
- But 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)
  - Specific example of Roy selection / selection on gains (heterogeneous treatment effects)
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
- Challenge: multiple dimensions of heterogeneity and imperfect competition
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)
  - Shepard (2016 JMP): Broader networks attract higher cost enrollees
Some open testing questions

- Impact of selection on contract design (a la Shepard; more work needed)
- 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...