Predictability and Predictiveness in Health Care Spending

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Motivation for paper
♦ Predictability of health care expenses is linked to “selection problems” in health insurance markets
♦ Consumers: People who expect high health costs buy more complete health insurance → “Adverse selection”
♦ Insurers: Health insurers try to attract the lowest expected cost group of enrollees → “Favorable selection”

Solution to the classic selection problem
♦ Pay plans or providers the expected total costs of their enrollees
♦ Agents no longer have an incentive to compete by avoiding high cost enrollees

How do competing health insurers influence who enrolls?

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertising</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Premiums (prices)</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Package of benefits to cover</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Choice of providers to contract with</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Service level distortions</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>
Alternative selection strategies

- TV advertisements showing healthy, active health plan members
- Subsidies for fitness club memberships in US and Australia
- Undersupply mental health providers in managed care
- Encouraging people to switch when the get a serious illness
  - US Medicare HMO members have 23 percent lower age-gender adjusted mortality rates than non HMO enrollees (This is too large a difference to be due to better management.)

Parallels in other markets

- Markets where there is fixed revenue but highly variable costs
- Sellers have a variety of dimensions to offer
  - Software support
  - Appliance service contracts
  - Car insurance
  - Labor markets

Key Concepts

Predictability
- How well can spending on a certain service be anticipated?

Predictiveness
- How well does expected spending on one type of service correlate with total spending?

Highly Predictable types of services
(easy to foresee use given a condition)

- Routine dental treatment
- Ear infection treatment for young children
- Eyeglass prescription renewals
- Diabetics use of insulin and blood sugar tests
- HIV/AIDS patient's use of drugs
- Mental health services
Highly Predictive types of services
(People using this service will tend to be expensive)

- Hospital services
- Malignant cancer treatment
- Diabetics use of insulin and blood sugar tests
- HIV/AIDS patient’s use of drugs
- Mental health services

Selection problems arise for services that are predictable and predictive!

Three literatures relevant

- Conventional risk adjustment
- Predictability of total health spending
- Optimal risk adjustment

Key insights of paper

- For some types of selection problems, it is the predictability and predictiveness of individual services rather than total medical spending that matters.
- Services for which the product of predictability and predictiveness is the highest will be most vulnerable to underprovision

Model of service level distortion
based on Frank Glazer and McGuire JHE (2000)

- Two types of health plans
  - Fee for service plan
  - HMO paid by capitation
- Consumers vary in severity of illness and preferences
- Consumers or plans or both have information on severity that is not available to regulator
- Closest in spirit to US Medicare program, ignoring fact that plans have limited ability to add extra benefits
**Sequence of moves**

1. Regulator chooses how to pay plans
2. Plans choose levels of services to offer
3. Consumers of different types choose between the HMO and the FFS
4. Consumers true health state is revealed, determining plan costs and consumer utility

**Medical Services (FGM)**

- $m_i$ = quantity of medical care to person $i$ on service $s$
- Marginal cost of $m = 1$ (units measured in dollars)
- $m_i = \{m_{i1}, m_{i2}, ..., m_{is}\}$ = actual quantities of each service
- $\hat{m}_i = \{\hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{is}\}$ = expected quantities of each service
- $M_i = \sum m_i$ = total health spending on all services
- Consumers differ in their need for services proportionally ⇒ plan chooses one rationing price $q_s$ for each service
- If the plan can differentiate service intensity by some observable variable, then we would consider each group a different service

**Demand curves for service $s$ by three consumers given rationing at price $q_s$**

- Maximise expected utility
- Choose HMO if $E_i[V(\hat{m}_i^{HMO})] > E_i[V(\hat{m}_i^{FFS})]$
- Let $n_i(\hat{m}_i)$ be the proportion of people of type $i$ choosing to join the HMO when levels of services $m_i$ are offered by the HMO.
- Since $\hat{m}_i(q)$ we can also write $n_i(\hat{m}_i(q))$
Health Plans

- Maximize expected profits by choosing the rationing price for each service, \( q = \{q_i\} \), where profits are

\[
\pi(q) = \sum_i n_i(\hat{m}_i(q)) \left[ r - \sum_s m_{is}(q_s) \right]
\]

- Notice that demand depends on foreseeable spending, while profits depend on actual spending on each service

Derivative of profit from tighter rationing

- Raising \( q_s \) for one service

\[
\frac{\partial \pi}{\partial q_s} = \eta_s q_s \sum_i \phi_i \hat{m}_{is} \tau_i - \eta_s \sum_i \eta_m m_{is}
\]

\[
\frac{\partial \pi}{\partial q_s} = \bar{m}_s \eta_s \left( \phi \sum_i \hat{m}_{is} \tau_i - 1 \right)
\]

\( I_s = \) Index of profitability of tighter rationing of service \( s \)

\[
I_s \equiv \frac{\partial \pi}{\partial q_s} \cdot \frac{\bar{M}}{\bar{m}_s}
\]

With further assumptions this translates into

\[
I_s = \eta_s \left( \phi \sum_i \hat{m}_{is} \tau_i - 1 \right)
\]

Using ordinary definitions

\[
\rho_{\bar{m}_s, \tau} = \frac{\sum_i \hat{m}_{is} \tau_i - \bar{m}_s \bar{\tau}}{\sigma_{\bar{m}_s} \sigma_{\bar{\tau}}}
\]

\[
I_s = \eta_s \sigma_{\bar{\tau}} \left( \frac{\sigma_{\bar{m}_s} \rho_{\bar{m}_s, \bar{\tau}} - 1}{\phi \sigma_{\bar{\tau}}} \right)
\]
\[ \tilde{I}_s = \text{renormalized index of selectivity} \]

profitability of tighter rationing of service \( s \)

\[ \tilde{I}_s = -\eta_s \left( \frac{\sigma_{\hat{m}_s}}{\bar{m}_s} \rho_{\hat{m}_s,M} - C \right) \]

**Key Analytical Result**

- The incentive to ration is determined by the Three things:
  - **predictability** (measured by the coefficient of variation of expected service spending)
  - **predictiveness** (measured by the correlation of expected service spending with total spending)
  - **Elasticity of demand** for service \( s (\eta_s) \)

- Services with a large selection index will tend to be rationed more tightly than average while others will be loosely rationed.

**Empirical Investigation**

- US Medicare data on elderly and disabled
- 1996 and 1997 insurance claims and eligibility data
- 5% national sample
- 1.47 million people

dependent variable = total health spending
Three empirical challenges to using this formulation

- We do not know what information plans use to predict both spending $m$, and the effect of spending on enrollment $n(m)$.
- We do not know which dimensions of health care spending are distorted by health plans to influence selection.
- We do not know the empirical specification used to make predictions.

Empirical methodology

- Estimate various models of total spending.
- Identify which sets of information are most predictive.
- Explore whether empirical specification matters.
- Estimate models of spending by type of service and by provider specialty using most highly predictive information set.
- Use predicted spending to calculate CV and Corr.
- Calculate selection indices.
- Show that rankings of service selection incentive is relatively invariant to specification.

Predictive power of various information sets

Dependent variable: 1997 total covered charges

<table>
<thead>
<tr>
<th>Weighted</th>
<th>Unweighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.011</td>
</tr>
<tr>
<td>Sample Mean</td>
<td>6,886</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1,380,863</td>
</tr>
<tr>
<td>R²</td>
<td>0.089</td>
</tr>
<tr>
<td>Diagnoses organized by DCC/HCC</td>
<td>0.104</td>
</tr>
<tr>
<td>Covered charges by DCC/HCC</td>
<td>0.099</td>
</tr>
<tr>
<td>Covered charges by Place of Service</td>
<td>0.149</td>
</tr>
<tr>
<td>Covered charges by Physician Specialty</td>
<td>0.142</td>
</tr>
<tr>
<td>Covered charges by Type of Service</td>
<td>0.150</td>
</tr>
<tr>
<td>All of the above except diagnoses</td>
<td>0.154</td>
</tr>
<tr>
<td>Kitchen sink: All of the above</td>
<td>0.169</td>
</tr>
</tbody>
</table>
Predictive power of various Specifications

Dependent variable: 1997 total covered charges

<table>
<thead>
<tr>
<th>Estimation method</th>
<th>Weighted OLS</th>
<th>OLS</th>
<th>Square Root model</th>
<th>Two Part linear model</th>
<th>link = log, dist = normal</th>
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</thead>
<tbody>
<tr>
<td>Partial Year Eligibles Included?</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Sample Mean</td>
<td>8,888</td>
<td>5,083</td>
<td>5,063</td>
<td>5,063</td>
<td>5,063</td>
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<td>1,273,471</td>
<td>1,273,471</td>
<td>1,273,471</td>
<td>1,273,471</td>
</tr>
<tr>
<td>Age and gender only</td>
<td>0.011</td>
<td>0.010</td>
<td>0.009</td>
<td>0.010</td>
<td>0.010</td>
</tr>
<tr>
<td>Prior year total covered charges</td>
<td>0.089</td>
<td>0.096</td>
<td>0.100</td>
<td>0.120</td>
<td>0.105</td>
</tr>
<tr>
<td>Diagnoses organized by DCC/HCC</td>
<td>0.104</td>
<td>0.108</td>
<td>0.102</td>
<td>0.107</td>
<td>0.105</td>
</tr>
<tr>
<td>Covered charges by DCC/HCC</td>
<td>0.099</td>
<td>0.107</td>
<td>0.101</td>
<td>0.105</td>
<td>0.095</td>
</tr>
<tr>
<td>Covered charges by Place of Service</td>
<td>0.143</td>
<td>0.143</td>
<td>0.133</td>
<td>0.143</td>
<td>0.139</td>
</tr>
<tr>
<td>Covered charges by Physician Specialty</td>
<td>0.142</td>
<td>0.152</td>
<td>0.129</td>
<td>0.152</td>
<td>0.131</td>
</tr>
<tr>
<td>Covered charges by Type of Service</td>
<td>0.150</td>
<td>0.155</td>
<td>0.143</td>
<td>0.154</td>
<td>0.134</td>
</tr>
<tr>
<td>All of the above except diagnoses</td>
<td>0.154</td>
<td>0.160</td>
<td>0.147</td>
<td>0.169</td>
<td>0.138</td>
</tr>
<tr>
<td>&quot;Kitchen sink&quot;: All of the above</td>
<td>0.169</td>
<td>0.171</td>
<td>0.157</td>
<td>0.169</td>
<td>0.147</td>
</tr>
</tbody>
</table>

Preliminary conclusions

♦ Functional form does not matter much for predictability of total spending
♦ Type of service is most highly predictive information set
♦ Adding additional variables to the information set does not increase predictability meaningfully
♦ In light of this, paper focuses on WLS results

"Predictability" of spending by type of service

<table>
<thead>
<tr>
<th>Type of Service (TOS) categories</th>
<th>Mean Spending in 1997</th>
<th>R² Using age, gender, lagged TOS spending</th>
<th>Std. Dev. of m̄ / mean of m̄</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospice</td>
<td>4.56</td>
<td>0.554</td>
<td>53.879</td>
</tr>
<tr>
<td>Home health care worker</td>
<td>525.13</td>
<td>0.451</td>
<td>3.902</td>
</tr>
<tr>
<td>Durable medical equipment</td>
<td>194.65</td>
<td>0.474</td>
<td>4.007</td>
</tr>
<tr>
<td>Inpatient visit facility charges</td>
<td>47.16</td>
<td>0.260</td>
<td>6.540</td>
</tr>
<tr>
<td>Intermediate care facility</td>
<td>14.66</td>
<td>0.013</td>
<td>4.449</td>
</tr>
<tr>
<td>Hospital visit by clinician</td>
<td>126.98</td>
<td>0.074</td>
<td>1.121</td>
</tr>
<tr>
<td>Home visit by clinician</td>
<td>25.10</td>
<td>0.274</td>
<td>2.680</td>
</tr>
</tbody>
</table>

Low "Predictability" services

<table>
<thead>
<tr>
<th>Type of Service</th>
<th>Mean ($)</th>
<th>R²</th>
<th>CV(\hat{m}_s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major Proc Cardiovascular</td>
<td>54.81</td>
<td>0.015</td>
<td>0.844</td>
</tr>
<tr>
<td>Minor Procedures</td>
<td>57.87</td>
<td>0.128</td>
<td>0.999</td>
</tr>
<tr>
<td>Anesthesia</td>
<td>34.31</td>
<td>0.024</td>
<td>0.512</td>
</tr>
<tr>
<td>Endoscopy</td>
<td>45.19</td>
<td>0.039</td>
<td>0.733</td>
</tr>
<tr>
<td>Major Procedure</td>
<td>38.63</td>
<td>0.008</td>
<td>0.562</td>
</tr>
<tr>
<td>Major Proc Orthopedic</td>
<td>32.31</td>
<td>0.009</td>
<td>0.673</td>
</tr>
<tr>
<td>Advanced Imaging - MRI</td>
<td>14.25</td>
<td>0.027</td>
<td>1.148</td>
</tr>
<tr>
<td>Eye Procedures</td>
<td>75.40</td>
<td>0.018</td>
<td>0.619</td>
</tr>
</tbody>
</table>
High Selection Index types of services (ignoring elasticity of demand)

<table>
<thead>
<tr>
<th>Type of Service</th>
<th>Predictability</th>
<th>Predictiveness</th>
<th>Selection Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospice</td>
<td>0.045</td>
<td>0.072</td>
<td>0.619</td>
</tr>
<tr>
<td>Home health care worker</td>
<td>0.083</td>
<td>0.072</td>
<td>1.148</td>
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<td>0.086</td>
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<td>0.733</td>
</tr>
<tr>
<td>Hospital Visit by clinician</td>
<td>0.121</td>
<td>0.318</td>
<td>0.356</td>
</tr>
<tr>
<td>Home Visit by clinician</td>
<td>0.268</td>
<td>0.130</td>
<td>0.348</td>
</tr>
<tr>
<td>Inpatient Facility (R&amp;B)</td>
<td>0.828</td>
<td>0.323</td>
<td>0.267</td>
</tr>
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Low Selection Index types of services (ignoring elasticity of demand)

<table>
<thead>
<tr>
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<th>Selection Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospice</td>
<td>0.539</td>
<td>0.048</td>
<td>2.578</td>
</tr>
<tr>
<td>Home health care worker</td>
<td>0.390</td>
<td>0.224</td>
<td>0.875</td>
</tr>
<tr>
<td>Durable Medical Equipment</td>
<td>4.007</td>
<td>0.175</td>
<td>0.703</td>
</tr>
<tr>
<td>Inpatient visit facility charge</td>
<td>6.540</td>
<td>0.091</td>
<td>0.592</td>
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</tr>
</tbody>
</table>
Rankings are remarkably stable across specifications

Fastest- and slowest-growing Private Health Insurance Ancillary benefits in Australia, 1996-2003

<table>
<thead>
<tr>
<th>Service</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sickness and Accident</td>
<td>1295%</td>
</tr>
<tr>
<td>Ex gratia Payments</td>
<td>775%</td>
</tr>
<tr>
<td>Other Services</td>
<td>627%</td>
</tr>
<tr>
<td>Fitness &amp; Lifestyle Courses/Equipment</td>
<td>609%</td>
</tr>
<tr>
<td>Natural Therapies</td>
<td>457%</td>
</tr>
<tr>
<td>Acupuncture / Acupressure</td>
<td>361%</td>
</tr>
<tr>
<td>Average, All Ancillaries</td>
<td>88%</td>
</tr>
<tr>
<td>Prostheses, Aids and Appliances</td>
<td>43%</td>
</tr>
<tr>
<td>Dietetics</td>
<td>33%</td>
</tr>
<tr>
<td>Accidental Death / Funeral Expenses</td>
<td>-7%</td>
</tr>
<tr>
<td>Travel and Accommodation</td>
<td>-19%</td>
</tr>
<tr>
<td>Community, Home, District Nursing</td>
<td>-66%</td>
</tr>
</tbody>
</table>

Conclusions - 1

- Knowing What was done (TOS=type of service) is modestly more informative than knowing Who did it, Why it was done, characteristics of Who it was done to, or Where it was done.
- Even if we give health plans all of the information evaluated here, there is relatively little improvement in predictive power ($R^2 = .17$) versus knowing only TOS ($R^2 = .15$).

Conclusions - 2

- Some services have high selection indices due to high predictability and high predictiveness:
  - Hospice, home health care, DME
  - Pulmonary diseases, oncology, ambulance, psychiatry
- Some services have low predictiveness which makes them attractive to overprovide:
  - Eye procedures, MRI
  - Chiropractic, gynecology
- Differences in selection indices across services are large enough to swamp likely differences in demand elasticities