Choosing Models for Cost Analyses: Issues of Nonlinearity and Endogeneity

Melissa M. Garrido,¹,² Partha Deb,³ James F. Burgess, Jr.,⁴,⁵ Joan D. Penrod¹,²

1. GRECC/REAP, James J Peters VA Medical Center, Bronx, NY
2. Brookdale Department of Geriatrics and Palliative Medicine, Mount Sinai School of Medicine
3. Department of Economics, Hunter College and the Graduate Center, City University of New York
4. Center for Organization, Leadership and Management Research, VA Boston Healthcare System
5. Department of Health Policy and Management, Boston University School of Public Health

Supported by Department Of Veteran Affairs, Health Services Research and Development Service (# IAD-06-060-2)
Cost Analyses and Comparative Effectiveness Research

“...The use and costs of health care are likely to be important outcomes of interventions for some patients, whether or not the results are used in a cost-effectiveness analysis.”

Garber A, Sox H. Health Affairs 2010; 29(10): 1805-1811

Health spending accounted for 17.6% of the GDP in 2009
Question #1 (Poll): How comfortable do you feel performing health care cost analyses?

- Very comfortable
- Somewhat comfortable
- Neither comfortable nor uncomfortable
- Somewhat uncomfortable
- Very uncomfortable
- N/A – Do not perform health care cost analyses
Issues in Healthcare Cost Analyses

• Skewed data
• Non-negative outcomes
• Censoring
• Endogeneity

• Distribution of marginal effects
Question #2 (Whiteboard): Which methods do you use to analyze costs?
How to Analyze Costs with an Endogenous Regressor?

• Models that use instrumental variables
  – Two-stage least squares on cost (2SLS)
  – Two-stage least squares on the natural log of costs (log-2SLS)
  – Control function models (special case: two-stage residual inclusion [2SRI])
  – Full information maximum simulated likelihood (FIMSL)

• Propensity score models
Example using Veterans Health Administration Data:

**Effect of an Inpatient Palliative Care Consultation on Costs**

- 3,321 inpatients hospitalized in five Veterans Affairs acute care facilities in 2004-2007 with one or more life-limiting diseases

- Data from VHA Medical SAS Inpatient Dataset and VA Decision Support System National Data Extract

- Outcome: Total direct costs per day during the inpatient admission
# Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>N (%) or Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Had a palliative care consultation</td>
<td>606 (18%)</td>
</tr>
<tr>
<td>65 or older</td>
<td>2235 (67%)</td>
</tr>
<tr>
<td>Advanced disease diagnosis*</td>
<td></td>
</tr>
<tr>
<td>Cancer</td>
<td>802 (24%)</td>
</tr>
<tr>
<td>HIV/AIDS</td>
<td>54 (2%)</td>
</tr>
<tr>
<td>Congestive heart failure</td>
<td>1541 (46%)</td>
</tr>
<tr>
<td>Chronic obstructive pulmonary disease</td>
<td>1699 (51%)</td>
</tr>
<tr>
<td>Number of comorbidities at initial hospitalization</td>
<td>2.1 (1.3)</td>
</tr>
<tr>
<td>Died during study period</td>
<td>1659 (50%)</td>
</tr>
<tr>
<td>Cost per day</td>
<td>$1235.27 ($749.36), IQR $813.74-$1433.82</td>
</tr>
<tr>
<td>Natural log of costs per day</td>
<td>7.01 (0.42), IQR 6.70-7.27</td>
</tr>
</tbody>
</table>

* Could have more than one diagnosis
Skewed Distribution of Costs

Mean = $1235.27
SD = $749.36
Median = $1021.92
IQR = $813.74 - $1433.82
Distribution of Natural Log of Costs

- Mean = 7.01
- SD = 0.42
- Median = 6.93
- IQR = 6.70-7.27
Instrumental variables for equations with a continuous outcome and endogenous binary treatment

\[ \Pr(d_i = 1 \mid z_i, I_i) = g(z_i \alpha + \delta I_i) \]

- Treatment
- Latent/Unobserved characteristics
- Distribution of error term
- Observed characteristics

\[ E(Y_i \mid x_i, d_i, I_i) = f(x_i \beta + \gamma d_i + \lambda I_i) \]

- Outcome (Cost)
- Distribution of error term
- Observed characteristics
Instrumental variables
for equations with a continuous outcome and endogenous
binary treatment

\[
\Pr(d_i = 1 \mid z_i, I_i) = g(z_i' \alpha + \delta I_i)
\]

\[
E(Y_i \mid x_i, d_i, I_i) = f(x_i' \beta + \gamma d_i + \lambda I_i)
\]

Treatment probability is endogenous due to common unobserved characteristics in each step (if neither \( \delta \) or \( \gamma = 0 \))
Instrumental variables
for equations with a continuous outcome and endogenous binary treatment

\[ \Pr(d_i = 1 \mid z_i, I_i) = g(z_i' \alpha + \delta I_i) \]
\[ E(Y_i \mid x_i, d_i, I_i) = f(x_i' \beta + \gamma d_i + \lambda I_i) \]

• 2SLS, Control Function, and Full Information Maximum Simulated Likelihood models are all based on these structural forms

• \( z \) must include at least one variable (the instrumental variable) that is not in \( x \)

• The instrumental variable must only be correlated with likelihood of treatment (\( d \)) and not with the likelihood of outcome (\( Y \))

• Each uses a different set of assumptions about \( f \) and \( g \)
Instrumental Variable

• Treatment: Palliative care (PC) consultation

• Outcome: Healthcare costs

• Instrumental variable: Propensity for requesting a PC consultation by an admitting physician
  – First-stage F statistic = 19.46, $p < .001$
  – Chi-square value for the Anderson canonical correlation likelihood ratio test $p < .001$
2SLS

Step 1: Model treatment likelihood, include instrumental variable

Step 2: Model outcome likelihood, include treatment likelihood from Step 1

• Often used because:
  • Simple
  • Minimal assumptions on distribution of error term

• Problems:
  • Grossly inefficient
  • Misleading estimates when used with skewed outcomes (costs)
Log-2SLS

- 2SLS, but with natural log transformation of cost

- Problem: Retransformation of outcome back to costs to calculate marginal effects
  - Taking antilog of predicted value will lead to biased estimates
  - Smearing estimators work only in the case of homoskedastic error terms or when there are few, easily identifiable sources of heteroskedasticity

Control Functions

Step 1: Model treatment likelihood, include instrumental variable

Step 2: Model outcome likelihood, include a function of the residuals of the treatment likelihood equation

- Uses principles of instrumental variable regression
- Flexible function of the residuals can produce the correct adjustment for endogeneity in the outcome equation
- No need to transform dependent variable

Control Functions: Choice of Residuals

Types of Residuals
- Response
  - Difference between predicted and observed treatment likelihood
- Anscombe
  - Include transformations of the predicted and observed treatment likelihoods that are aimed at achieving normality
- Deviance
  - Obtained from a function of the log likelihood ratio

• These are equivalent in linear but not nonlinear settings
• Anscombe and deviance residuals better approximate a normal distribution in nonlinear settings

Special Case of Control Function Approach: 2SRI

Step 1: Model treatment likelihood, include instrumental variable

Step 2: Model outcome likelihood, include the *response residual* of the treatment likelihood equation

Lee S. Journal of Econometrics 2007; 141: 1131-1158

Often a misapplication of CF: No reason to believe that including just the response residual eliminates endogeneity bias

More research needed to determine which functional form and specification of the residuals is needed for CF to behave optimally in nonlinear studies

Basu A, Manning WG. Medical Care 2009; 47: S109-S114
Full Information Maximum Simulated Likelihood (FIMSL)

\[
Pr(d_i = 1 \mid z_i, I_i) = g(z_i' \alpha + \delta I_i) \\
E(Y_i \mid x_i, d_i, I_i) = f(x_i' \beta + \gamma d_i + \lambda I_i)
\]

- Derive the joint distribution of the treatment and outcome variables conditional on the common latent variables (I_i)
- Define and maximize a simulated likelihood function
- Estimate treatment effect with draws from a pseudo-random Halton sequence and average these effects

Propensity Scores

• Pros:
  • Accounts for selection into treatment based on observable characteristics

• Cons:
  • Little is known about the performance of propensity scores in nonlinear models
    – May not be able to balance distributions of covariates between those who did and did not receive treatment

Mean days until death

Deciles of propensity scores

SD days until death

Deciles of propensity scores
<table>
<thead>
<tr>
<th>Model</th>
<th>Median</th>
<th>Mean</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Two Stage Least Squares</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost</td>
<td>-3185.83</td>
<td>-3185.83</td>
<td>(-3185.83, -3185.83)</td>
</tr>
<tr>
<td>Natural log of cost (retransformed)</td>
<td>-1347.77</td>
<td>-1514.07</td>
<td>(-3866.82, -464.14)</td>
</tr>
<tr>
<td><strong>Propensity Score</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nearest neighbor</td>
<td>-129.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stratification</td>
<td>-95.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Control Function Approach</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Response – 1st degree (2SRI)</td>
<td>-152.33</td>
<td>-153.68</td>
<td>(-254.73, -70.95)</td>
</tr>
<tr>
<td>Response – 3rd degree</td>
<td>-217.64</td>
<td>-220.06</td>
<td>(-388.65, -100.49)</td>
</tr>
<tr>
<td>Anscombe – 1st degree</td>
<td>-75.29</td>
<td>-75.94</td>
<td>(-125.44, -35.76)</td>
</tr>
<tr>
<td>Anscombe – 3rd degree</td>
<td>-319.64</td>
<td>-324.62</td>
<td>(-625.05, -146.66)</td>
</tr>
<tr>
<td>Deviance – 1st degree</td>
<td>-133.34</td>
<td>-134.40</td>
<td>(-221.17, -62.47)</td>
</tr>
<tr>
<td>Deviance – 3rd degree</td>
<td>-439.39</td>
<td>-450.02</td>
<td>(-972.33, -198.25)</td>
</tr>
<tr>
<td><strong>Full Information MSL</strong></td>
<td>-422.92</td>
<td>-429.38</td>
<td>(-733.09, -193.93)</td>
</tr>
</tbody>
</table>
Importance of Distribution of Marginal Effects

• Partial effects differ across observations in nonlinear models

• Where and for whom the marginal effect is calculated depends on the research question
Marginal Effects of PC Consultation on Direct Costs per Day

Density

Cost ($)

Log-2SLS
2SLS
FIMSL
CF, 3rd degree Anscombe residuals
CF, 1st degree response residuals (2SRI)
Marginal Effects of PC Consultation on Direct Costs per Day

- CF, 1st degree response residuals (2SRI)
- CF, 3rd degree deviance residuals
- CF, 3rd degree Anscombe residuals
- FIMSL
- PS, nearest neighbor
Summary

• Estimates from the FIMSL model were the most similar to those of the CF 3rd degree Anscombe and deviance residuals

• Clustering of these three estimate distributions suggests that we have robust estimates of the effect of PC consultations on costs

• FIMSL provided similar results to CF without the need for several specification tests and with lower variance for estimates

• Further testing with other datasets is needed to determine how often FIMSL results mirror those from CF models
Recommendations for Health Care Cost Analyses

• Obtain estimates from several models to check for robustness of results

• Evaluate robustness by examining distributions of marginal effects

• Account for nonlinearity and endogeneity at the same time
Questions?

For list of references or other questions, please e-mail me at melissa.garrido@va.gov

The views expressed in this presentation are those of the authors and do not necessarily reflect the position or policy of the Department of Veterans Affairs or the United States government.