Instrumental variable methods for evaluating healthcare interventions using SAS

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Wisconsin Illinois SAS® Users

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Healthcare Expenditures in the U.S.

- Rose from 13% of GDP in 2000 to 18% in 2011 (World Bank)
- This rate of increase is unsustainable

Source: Centers for Medicare and Medicaid Services
“Bending the Cost Curve”

- Many interventions have tried to reduce healthcare spend, e.g.,
  1. Disease management programs aimed at closing gaps in care
  2. Interventions to prevent avoidable utilization
  3. Value based care models (including patient centered medical homes and accountable care organizations)

- What works?
This Presentation: Outline

- The problem
  - Evaluating interventions to reduce healthcare spend
  - Are “gatekeeper” insurance plans a potential solution?
- Observational studies
  - Reasons why
  - Approaches to adjusting for unobserved group differences
- Study design and MEPS data
- Results
- Conclusions
**What is a “Gatekeeper” Insurance Plan?**

Basically, all of a person’s healthcare is managed through a “gatekeeper” physician, financially incented to deliver efficient care.

Some typical key differences between GK and NGK plans:

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Gatekeeper (GK) plans</th>
<th>Non-gatekeeper (NGK) plans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Care management</td>
<td>Care managed through single source (e.g., primary care physician)</td>
<td>Care not managed through single source (patient directs own care)</td>
</tr>
<tr>
<td>Physician payment</td>
<td>Often involves component of fixed per-patient payment</td>
<td>Fee-for-service (payment per procedure)</td>
</tr>
<tr>
<td>Specialist referrals</td>
<td>Through primary care physician</td>
<td>Patient self-referrals</td>
</tr>
</tbody>
</table>
Do GK Plans Reduce Healthcare Expenditures? How Would We Know?

- Ideally -- randomize people to either a GK or NGK insurance plan, and watch what happens over time to the two groups.
- However, people (understandably) object to being randomized to insurance plans!
  - *This is a good example of a situation where randomized study is unfeasible.*
- So how can we study this? What are the alternatives?
  - There are many – some not so good (e.g., pre-post with no control)
  - Frequently recommended: Observational study
Observational Studies

- Observational studies typically capitalize on existing data (e.g., claims data, surveys, disease registries) to examine how variation in a characteristic is associated with variation in an outcome (Stroup et al, 2000).
- Need control group representing the counterfactual
- **Problem**: Self-selection bias
- **Solution**: Adjust for group differences (intervention vs. control) in pre-intervention ("baseline") characteristics
- **Typical methods**: Regression, matching, instrumental variable methods
Instrumental Variable Methods

- What is endogeneity?
  - Consider the simple linear model: $Y_i = \beta_0 + \beta_1 X_1 + \epsilon_i$
  - In OLS regression, the assumption of $E(X_i \epsilon_i) = 0$ (exogeneity of $X$), among several others, renders the OLS estimator of $\beta_1$ BLUE (Best Linear Unbiased Estimator).
  - A regressor $X$ is **endogenous** when it is correlated with the error term $\epsilon$. That means: $E(X_i \epsilon_i) \neq 0$
  - **This results in biasedness and/or inconsistency of the OLS estimator!**
Endogeneity: Examples

- Mortality from heart attacks as a function of treatment intensity (TI)
  - What if TI is a function of unobservable health status?
- Current consumption regressed on current income
  - What if income is measured with error?
- Market equilibrium reached by adjusting prices and quantities
  - What if both P and Q move simultaneously?
- Time series regression of health care spend at time T on prior periods’ expenditures (e.g. T-1, T-2, …)
  - What if lagged dependent variables are included as regressors?
Main Causes of Endogeneity

- Omitted Variable Bias (selection bias)
- Measurement Error
- Simultaneous Causality (Reverse Causality)
- Lagged values of DV used as regressors, with serial correlation present
Consequences of Endogeneity

- Omitting a variable ($X_2$) creates a bias in $\hat{\beta}_1$ if:
  - $X_2$ is correlated with $Y$ (becomes part of $\epsilon$ when omitted) and
  - $X_2$ is correlated with $X_1$ (leading to $E(X_i\epsilon_i) \neq 0$)
- Measurement error leads to attenuation bias ($\hat{\beta}_1$ is biased towards 0) since we observe $M_i = X_i + \nu_i$ instead of $X_i$.
- Simultaneous causality leads to $E(X_i\epsilon_i) \neq 0$ as well.
- Lagged dependent variables as regressors will, in the presence of serial correlation, lead to a correlation between $Y_{t-1}$ with $\epsilon_t$, for example.
Goals of This Study

1. Illustrate the implementation of several observational study approaches using SAS
   - Naïve regression
   - Instrumental variable regression
   - Propensity matching
2. Discuss practical tradeoffs of different approaches
3. Illustrate the approaches using MEPS data to compare healthcare expenditures for individuals in GK vs. NGK insurance plans
Study Design

- *Estimate outcomes associated with participating in private GK vs. NGK plans*
  1. Identify individuals in private GK plans and private NGK plans at the end of 2009
  2. Use methods to adjust for group differences in baseline medical spend and other characteristics measured earlier in 2009
  3. Examine group differences in medical spend across 2010

- **Hypothesis:** Being in a private GK plan will be associated with lower healthcare expenditures
Data: Medical Expenditure Panel Survey (MEPS)

- Longitudinal, national probability survey (5 “rounds” of data collection per participant across 2 years)
- Focuses on health and healthcare
- Conducted by Agency for Healthcare Research and Quality under U.S. Dept. of Health and Human Services
- Data is available to the public
- Data for this study: MEPS panel 14 (2009-2010)
- Only past study of GK vs. NGK using MEPS was Hromadkova (2011)
Analysis of the GK vs. NGK Effect

- **Dependent variable**: Total healthcare spend, 2010 (log transformed)
- **Group variable**: GK vs. NGK insurance plan, end of 2009
- **Baseline characteristics** measured earlier in 2009 (2009 healthcare spend, health, demographics, have usual care provider, usual care provider is primary care physician)
- The group difference was estimated using 3 methods:
  1. Naïve regression
  2. Instrumental variable regression
  3. Propensity matching
Steps in Instrumental Variable Regression (Two Stage Least Squares)

1. **Identify the instrumental variable**, “IV” (in addition to other variables needed for analysis, e.g., outcome variable, covariates, treatment indicator)

2. **“Stage 1”**: Create fitted values from a regression model where IV is the outcome variable

3. **“Stage 2”**: Create model of the outcome variable, using Stage 1 fitted values as well as other covariates as the predictors
How to Choose an IV?

- Needs to meet certain conditions, e.g.:
  1. Associated with treatment variable
  2. Not associated with outcome after taking treatment variable into account
  3. Not correlated with error term in the model

- Some assumptions are typically not confirmable (e.g., #3), so need to base on theory or literature
IVs Used in Past Studies of Outcomes of Insurance Type

1. Percent participation in insurance type within state (Rivera-Hernandez, Mor, Galarraga)
2. Individual’s self-employment status (Meer & Rosen, 2002)
3. Number of large organizations in which an individual is a member (a marker for insurance type in Vietnam; Jowett, Deolalikar, Martinsson, 2004)
IV Used in This Study

- % of individuals with GK insurance within the local region/MSA combination
  - MSAs – roughly, urban areas
  - Regions – Northeast, Midwest, South, West
* Compute IV;
  data inscope2;
  set inscope;
  if region2<0 or msa2<0 then region2_msa2=0;
  else if msa2=0 then do;
    if region2=1 then region2_msa2=10;
    else if region2=2 then region2_msa2=20;
    else if region2=3 then region2_msa2=30;
    else if region2=4 then region2_msa2=40;
  end;
  else if msa2=1 then do;
    if region2=1 then region2_msa2=11;
    else if region2=2 then region2_msa2=21;
    else if region2=3 then region2_msa2=31;
    else if region2=4 then region2_msa2=41;
  end;
  run;

* Percent with private GK in region/MSA;
  proc univariate data=inscope2 noprint;
  class region2_msa2;
  var prv_gatekeeper_y1;
  output out=a mean=region_msa_mean_gk;
  run;

  proc sort data=inscope2;
  by region2_msa2;
  run;

  data inscope3;
  merge inscope2(in=a) a;
  by region2_msa2;
  if a;
  run;
## Values of the IV

<table>
<thead>
<tr>
<th>Region</th>
<th>In MSA</th>
<th>Not MSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>52%</td>
<td>31%</td>
</tr>
<tr>
<td>Midwest</td>
<td>42%</td>
<td>38%</td>
</tr>
<tr>
<td>South</td>
<td>42%</td>
<td>16%</td>
</tr>
<tr>
<td>West</td>
<td>62%</td>
<td>24%</td>
</tr>
</tbody>
</table>
* First stage;
proc reg data=inscope3;
model prv_gatekeeper_y1 = region_msa_mean_gk totexpyl &addl_adj;
output out=inscope4 predicted=yhat;
run; quit;

* Second stage;
proc reg data=inscope4;
model ln_totexpyl = yhat totexpyl &addl_adj / vif;
run; quit;

* Naive OLS regression;
proc reg data=inscope4;
model ln_totexpyl = prv_gatekeeper_y1 totexpyl &addl_adj / vif;
run; quit;
SAS Code Excerpts (Cont’d)

```
proc syslin data=inscope4 2sls;
endogenous prv_gatekeeper_y1;
instruments region_msa_mean_gk totexpyl &addl_adj;
model ln_totexpyl2 = prv_gatekeeper_y1 totexpyl &addl_adj;
Run;
```

This yields more accurate standard errors, but requires SAS/ETS (cannot be done in SAS/STAT)
Alternatives to PROC SYSLIN

- %PROC_R macro to run analysis in R
- PROC IML or SAS/IML Studio using SUBMIT / R and ENDSUBMIT statements with R code sandwiched in between them.
  - Search SAS Help for “Calling R Functions from PROC IML”
- Create SAS transport data set, read it into R using the package foreign and read.xport() function.
## Results: Outcome Description

### Original scale (mean healthcare spend, per person per year)

<table>
<thead>
<tr>
<th>Insurance</th>
<th>Healthcare spend</th>
</tr>
</thead>
<tbody>
<tr>
<td>GK</td>
<td>$3,363</td>
</tr>
<tr>
<td>NGK</td>
<td>$3,992</td>
</tr>
</tbody>
</table>

### Log-dollars scale

<table>
<thead>
<tr>
<th>Insurance</th>
<th>Healthcare spend</th>
</tr>
</thead>
<tbody>
<tr>
<td>GK</td>
<td>6.2</td>
</tr>
<tr>
<td>NGK</td>
<td>6.6</td>
</tr>
</tbody>
</table>
## Results: Adjusted Models

<table>
<thead>
<tr>
<th>Method</th>
<th>Parameter estimate</th>
<th>Standard error</th>
<th>95% CI</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve regression</td>
<td>-0.37</td>
<td>0.0612</td>
<td>-0.49, -0.25</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>2-stage least squares</td>
<td>-0.44</td>
<td>0.2546</td>
<td>-0.93, 0.05</td>
<td>0.0841</td>
</tr>
<tr>
<td>PROC SYSLIN</td>
<td>-0.44</td>
<td>0.2540</td>
<td>-0.93, 0.05</td>
<td>0.0834</td>
</tr>
<tr>
<td>Propensity matching</td>
<td>-0.36</td>
<td>0.0637</td>
<td>-0.48, -0.24</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

Estimates shown in the table are on the log-dollars scale.
Conclusions

- All methods yielded parameter estimates within the same ballpark, but standard errors varied widely.
- All methods indicated that being enrolled in a private GK plan was associated with lower healthcare spend in the following year – but IV methods reflected greater uncertainty about the estimate.
Recommendations

- Results are sensitive to the methods used to adjust for baseline differences
- Be aware of the assumptions underlying the method that you choose -- and the potential impact on results
- Consider using a “primary analysis” with a specific method chosen a priori, to avoid cherry picking results
- Use other methods as secondary, sensitivity analyses