Estimation of Treatment Effects in Repeated Public Good Experiments

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Comments Welcomed

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Objectives

• Show empirical evidences of
  – Mann-Whitney-Wilcoxon’s Rank Sum Tests (nonparametric rank test) reject too often
  – Dynamic Panel Censored regressions reject too less
  – Eyeball Examination works relatively well

• Provide a new statistical method to measure and test treatment effects
  – Develop Asymptotic Theory
  – Show the new test works very well in practice.
# Empirical Examples and Data

Table 1: Data Source: Andreoni (1988, 95a, 95b)

<table>
<thead>
<tr>
<th>Name</th>
<th>Reg1</th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>95a,95b</td>
<td>88</td>
<td>95b</td>
<td>95a</td>
<td>88</td>
</tr>
<tr>
<td>Total subjects</td>
<td>3×20</td>
<td>2×20</td>
<td>2×20</td>
<td>2×20</td>
<td>2×15</td>
</tr>
<tr>
<td>Rounds</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Group Size</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Group Return</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Individual Return (own, group)</td>
<td>(1,0)</td>
<td>(1,0)</td>
<td>(1,0)</td>
<td>(1,-0.5)</td>
<td>(1,0)</td>
</tr>
<tr>
<td>Members Within A Group</td>
<td>stranger</td>
<td>stranger</td>
<td>stranger</td>
<td>stranger</td>
<td>Partner</td>
</tr>
<tr>
<td>Extra Information</td>
<td>n.a</td>
<td>n.a</td>
<td>Rank</td>
<td>n.a</td>
<td>n.a</td>
</tr>
<tr>
<td>No. of Tokens</td>
<td>60</td>
<td>50</td>
<td>60</td>
<td>60</td>
<td>50</td>
</tr>
</tbody>
</table>
Existential Empirical Methods

- Eyeball Examination
- Mann-Whitney-Wilcoxon’s Rank Sum Test
- Panel Censored (Tobit) Regression
- Dynamic Panel Regression
Effectiveness of Eyeball Exam

![Graph showing the effectiveness of Eyeball Exam over different rounds. The graph plots the fraction of the endowment contributed to the public good against rounds. Different lines represent different conditions: Reg1, Reg2, RegR, Neg, and Part.](image)
Effectiveness of Eyeball Exam

**Effective Case: No Crossing Over**

**Non-Effective Case: Crossing over at least one time.**
Non-Effective Case

Case 1: Reg1 v.s. Reg2

![Graph showing the fraction of the endowment contributed to the public good over rounds for Reg1 and Reg2.](image-url)
Effective Case: Yes

Case 2: Reg1 v.s. RegR

[Graph showing the fraction of the endowment contributed to the public good over rounds for Reg1 and RegR]
Effective Case
Case 3: Reg1 v.s. Neg

The graph shows the fraction of the endowment contributed to the public good over 10 rounds for two groups, Reg1 and Neg. The fraction decreases significantly for both groups as the rounds progress, but the decrease is more pronounced for Neg compared to Reg1.
Effective Case

Case 4: Reg1 v.s. Part

![Graph showing the fraction of the endowment contributed to the public good over rounds.](image-url)
Effective Case
Case 5: Reg2 v.s. RegR
Effective Case
Case 6: Reg2 v.s. Neg

[Graph showing the fraction of the endowment contributed to the public good over rounds for two groups: Reg2 and Neg.]
Effective Case

Case 7: Reg2 v.s. Part

![Graph showing the fraction of the endowment contributed to the public good over rounds for Reg2 and Part.](image)

- **Reg2** (filled circles) shows a steady decline in the fraction contributed, starting from a high value and decreasing to a lower value by the end of the rounds.
- **Part** (triangle markers) exhibits a more erratic pattern with fluctuations, starting from a lower value and showing an overall decrease but with some peaks and troughs.
Non-Effective Case
Case 8: RegR v.s. Neg

Fraction of the Endowment Contributed to the Public Good

Round

1 2 3 4 5 6 7 8 9 10
### Eyeball Exam: Summary

<table>
<thead>
<tr>
<th>Controlled Treated</th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Reg2 v.s.</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>RegR v.s.</th>
<th>Neg</th>
<th>Part</th>
<th>Neg v.s.</th>
<th>Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>TE Effects</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Part</td>
</tr>
</tbody>
</table>
Eyeball Exam: Summary

<table>
<thead>
<tr>
<th>Controlled Treated</th>
<th>Reg2</th>
<th>Reg1 v.s.</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Reg2 v.s.</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>RegR v.s.</th>
<th>Neg</th>
<th>Part</th>
<th>Neg v.s.</th>
<th>Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>TE Effects</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

Cross-over cases

Eyeball Exam is not effective when two outcomes are crossing over each other
Mann-Whitney-Wilcoxon Rank Test

• Very popular. Why?
  – Easy to use
  – Nonparametric test: Distribution free test
  – Easy to reject the null of no treatment effect.

• Any (known) econometric issue?
  – Requires strictly stationary: cross sectional variance should be same across round.
  – Requires strong stochastic dominance: No overlapping outcome.
## Mann-Whitney-Wilcoxon Rank Rank Test

Table 2: Validity of Mann-Whitney-Wilcoxon Rank Sum Test (z-score)

<table>
<thead>
<tr>
<th>Cases</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reg1, Reg2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.11</td>
</tr>
<tr>
<td>2. Reg1, RegR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-11.7</td>
</tr>
<tr>
<td>3. Reg1, Neg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-14.4</td>
</tr>
<tr>
<td>4. Reg1, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-10.3</td>
</tr>
<tr>
<td>5. Reg2, RegR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-8.99</td>
</tr>
<tr>
<td>6. Reg2, Neg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-12.6</td>
</tr>
<tr>
<td>7. Reg2, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-6.66</td>
</tr>
<tr>
<td>8. RegR, Neg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.49</td>
</tr>
<tr>
<td>10. Neg, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.68</td>
</tr>
</tbody>
</table>
## Mann-Whitney-Wilcoxon Rank Test

### Table 2: Validity of Mann-Whitney-Wilcoxon Rank Sum Test (z-score)

<table>
<thead>
<tr>
<th>Cases</th>
<th>Round 1</th>
<th>Round 2</th>
<th>Round 3</th>
<th>Round 4</th>
<th>Round 5</th>
<th>Round 6</th>
<th>Round 7</th>
<th>Round 8</th>
<th>Round 9</th>
<th>Round 10</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reg1, Reg2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.11</td>
</tr>
<tr>
<td>2. Reg1, RegR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-11.7</td>
</tr>
<tr>
<td>3. Reg1, Neg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-14.4</td>
</tr>
<tr>
<td>4. Reg1, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-10.3</td>
</tr>
<tr>
<td>5. Reg2, RegR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-8.99</td>
</tr>
<tr>
<td>6. Reg2, Neg</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-12.6</td>
</tr>
<tr>
<td>7. Reg2, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-6.66</td>
</tr>
<tr>
<td>8. RegR, Neg</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.49</td>
</tr>
<tr>
<td>10. Neg, Part</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.68</td>
</tr>
</tbody>
</table>

Reject the null hypothesis for cases with absolute values greater than 1.96. Not Reject for cases with absolute values less than 1.96.
Table 2: Validity of Mann-Whitney-Wilcoxon Rank Sum Test (z-score)

<table>
<thead>
<tr>
<th>Cases</th>
<th>Round 1</th>
<th>Round 2</th>
<th>Round 3</th>
<th>Round 4</th>
<th>Round 5</th>
<th>Round 6</th>
<th>Round 7</th>
<th>Round 8</th>
<th>Round 9</th>
<th>Round 10</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reg1, Reg2</td>
<td>-2.60</td>
<td>-2.19</td>
<td>-1.56</td>
<td>-1.23</td>
<td>-0.49</td>
<td>-0.05</td>
<td>-0.05</td>
<td>-0.22</td>
<td>-0.88</td>
<td>-0.95</td>
<td></td>
</tr>
<tr>
<td>2. Reg1, RegR</td>
<td>-2.49</td>
<td>-1.91</td>
<td>-4.25</td>
<td>-3.64</td>
<td>-3.87</td>
<td>-4.91</td>
<td>-5.54</td>
<td>-4.95</td>
<td>-5.19</td>
<td>-4.01</td>
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</tr>
<tr>
<td>3. Reg1, Neg</td>
<td>-4.57</td>
<td>-5.08</td>
<td>-5.67</td>
<td>-4.81</td>
<td>-5.00</td>
<td>-5.08</td>
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<td>-4.23</td>
<td>-4.93</td>
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</tr>
<tr>
<td>5. Reg2, RegR</td>
<td>-0.70</td>
<td>-0.91</td>
<td>-2.50</td>
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<td>-3.65</td>
<td>-4.24</td>
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<tr>
<td>6. Reg2, Neg</td>
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<tr>
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<td>-2.59</td>
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<td>-1.59</td>
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</tr>
<tr>
<td>8. RegR, Neg</td>
<td>-3.02</td>
<td>-3.00</td>
<td>-3.10</td>
<td>-1.04</td>
<td>-1.94</td>
<td>-1.30</td>
<td>-0.35</td>
<td>2.08</td>
<td>2.68</td>
<td>1.30</td>
<td></td>
</tr>
<tr>
<td>9. RegR, Part</td>
<td>-0.28</td>
<td>-0.94</td>
<td>0.29</td>
<td>0.55</td>
<td>0.88</td>
<td>0.90</td>
<td>1.20</td>
<td>1.81</td>
<td>2.75</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>10. Neg, Part</td>
<td>1.12</td>
<td>1.86</td>
<td>2.31</td>
<td>2.02</td>
<td>2.38</td>
<td>2.38</td>
<td>0.96</td>
<td>1.14</td>
<td>1.72</td>
<td>4.93</td>
<td></td>
</tr>
</tbody>
</table>
# MWW & Eyeball Tests

<table>
<thead>
<tr>
<th>Controlled Treated</th>
<th>Reg2</th>
<th>Reg1 v.s.</th>
<th>Reg2 v.s.</th>
<th>RegR v.s.</th>
<th>Neg v.s.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eye Ball</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>?</td>
<td>Yes</td>
</tr>
<tr>
<td>MWWW</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>
Dynamic Censored Regressions

Model
\[ y_{it}^* = a_0 + \varnothing d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]
\[ f(t) = t \text{ or } 1/t \]
\[ y_{it} = \begin{cases} 
1 & \text{if } y_{it}^* > 1 \\
y_{it}^* & \text{if } 0 \leq y_{it}^* \leq 1 \\
0 & \text{if } y_{it}^* < 0 
\end{cases} \]
\[ d_i = \begin{cases} 
1 & \text{if } y_{it} \text{ is controlled,} \\
0 & \text{if } y_{it} \text{ is treated.} 
\end{cases} \]
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \delta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ f(t) = t \text{ or } 1/t \]

\[ y_{it} = \begin{cases} 
1 & \text{if } y_{it}^* > 1 \\
y_{it}^* & \text{if } 0 \leq y_{it}^* \leq 1 \\
0 & \text{if } y_{it}^* < 0 
\end{cases} \]

\[ d_i = \begin{cases} 
1 & \text{if } y_{it} \text{ is controlled,} \\
0 & \text{if } y_{it} \text{ is treated.} 
\end{cases} \]
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \varphi d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ f(t) = t \text{ or } 1/t \]

\[ y_{it} = \begin{cases} 
1 & \text{if } y_{it}^* > 1 \\
y_{it}^* & \text{if } 0 \leq y_{it}^* \leq 1 \\
0 & \text{if } y_{it}^* < 0 
\end{cases} \]

Unknown and Latent, Modeled by all observed variables

\[ d_i = \begin{cases} 
1 & \text{if } y_{it} \text{ is controlled,} \\
0 & \text{if } y_{it} \text{ is treated.}
\end{cases} \]
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \delta d_i + \rho y_{it-1} + \delta (\tilde{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ f(t) = t \text{ or } 1/t \]

\[ y_{it} = \begin{cases} 
1 & \text{if } y_{it}^* > 1 \\
y_{it}^* & \text{if } 0 \leq y_{it}^* \leq 1 \\
0 & \text{if } y_{it}^* < 0 
\end{cases} \]

\[ d_i = \begin{cases} 
1 & \text{if } y_{it} \text{ is controlled,} \\
0 & \text{if } y_{it} \text{ is treated.} 
\end{cases} \]

Observed, Used in Eyeball & MWW test

Unknown and Latent, Modeled by all observed variables
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \vartheta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ H_0 : \vartheta = 0 \iff \text{No Treatment effects} \]
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \delta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ H_0 : \delta = 0 \iff \text{No Treatment effects} \]

Really? Consider the following two regressions.

\[ y_{it}^* = a_0 + \delta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it} \tag{3} \]

\[ y_{it} = a_0 + \delta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it} \tag{5} \]

Tobit or Censored

Uncensored or Dynamic Panel Regressions
Dynamic Censored Regressions

Model

\[ y_{it}^* = a_0 + \vartheta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ H_0 : \vartheta = 0 \iff \text{No Treatment effects} \]

Really? Consider the following two regressions.

\[ y_{it}^* = a_0 + \vartheta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it} \quad (3) \]

\[ y_{it} = a_0 + \vartheta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it} \quad (5) \]

\[ H_0 : E(y_{\tau,it}) = E(y_{c,it}) \iff H_0^* : E(y_{\tau,it}^*) = E(y_{c,it}^*) \]

\[ H_0 : \vartheta = 0 \text{ in (5)} \quad \quad H_0^* : \vartheta = 0 \text{ in (3)} \]
Dynamic Censored Regressions

Model
\[ y_{it}^* = a_0 + \vartheta d_i + \rho y_{it-1} + \delta(\bar{y}_{it-1} - y_{it-1}) + \phi f(t) + e_{it}, \]

\[ H_0 : \vartheta = 0 \iff \text{No Treatment effects} \]

Used in Eyeball & MWW.
Null: No Treatment Effects

\[ H_0 : E(y_{\tau, it}) = E(y_{c, it}) \iff H_0^* : E(y_{\tau, it}^*) = E(y_{c, it}^*) \]

\[ H_0 : \vartheta = 0 \text{ in (5)} \]

\[ H_0^* : \vartheta = 0 \text{ in (3)} \]
Examples 1: Consider the following simple censored model

\[ y_{s,i}^* = a_s + \epsilon_{s,i} \text{ for } s = c \text{ or } \tau \]

Assume \( \epsilon_{s,i} \sim iidN(0, \sigma^2) \)

| \( \sigma^2 \) | \( \text{E}(y^*) \) | \( \text{Pr}(y^* < 0) \) | \( \text{Pr}(0 \leq y^* \leq 1) \) | \( \text{Pr}(y^* > 1) \) | \( \text{E}(y^* | 0 \leq y^* \leq 1) \) | \( \text{E}(y) \) |
|---|---|---|---|---|---|---|
| Case A | 2 | 0.5 | 0.362 | 0.276 | 0.362 | 0.138 | 0.421 |
| Case B | 1 | 0.5 | 0.309 | 0.383 | 0.309 | 0.192 | 0.382 |
Dynamic Censored Regressions

Examples 1: Consider the following simple censored model

\[ y_{s,i}^* = a_s + \epsilon_{s,i} \text{ for } s = c \text{ or } \tau \]

Assume \( \epsilon_{s,i} \sim iidN(0, \sigma^2) \)

<table>
<thead>
<tr>
<th>( \sigma^2 )</th>
<th>E(( y^* ))</th>
<th>Pr(( y^* &lt; 0 ))</th>
<th>Pr(0 \leq y^* \leq 1)</th>
<th>Pr(( y^* &gt; 1 ))</th>
<th>E(( y^* \mid 0 \leq y^* \leq 1 ))</th>
<th>E(y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case A</td>
<td>2</td>
<td>0.5</td>
<td>0.362</td>
<td>0.276</td>
<td>0.362</td>
<td>0.138</td>
</tr>
<tr>
<td>Case B</td>
<td>1</td>
<td>0.5</td>
<td>0.309</td>
<td>0.383</td>
<td>0.309</td>
<td>0.192</td>
</tr>
</tbody>
</table>

Yes, Case A > Case B
If you use eyeball, & MWW
=> Reject H₀
Dynamic Censored Regressions

Examples 1: Consider the following simple censored model

\[ y_{s,i}^* = a_s + \epsilon_{s,i} \text{ for } s = c \text{ or } \tau \]

Assume \( \epsilon_{s,i} \sim iidN(0, \sigma^2) \)

| \( \sigma^2 \) | \( E(y^*) \) | \( \Pr(y^* < 0) \) | \( \Pr(0 \leq y^* \leq 1) \) | \( \Pr(y^* > 1) \) | \( E(y^* | 0 \leq y^* \leq 1) \) | \( E(y) \) |
|---------|---------|---------|----------------|----------------|----------------|---------|
| Case A 2 | 0.5     | 0.362   | 0.276          | 0.362          | 0.138          | 0.421   |
| Case B 1 | 0.5     | 0.309   | 0.383          | 0.309          | 0.192          | 0.382   |

No Treatment effects.
Case A = Case B
If you use censored regressions
\( \Rightarrow \) Can’t reject \( H_0^* \)

Yes, Case A > Case B
If you use eyeball, & MWW
\( \Rightarrow \) Reject \( H_0 \)
Dynamic Censored Regressions

Table 3: Dynamic Tobit and Panel Regressions with Random Effects

<table>
<thead>
<tr>
<th>Controlled</th>
<th>Reg1 v.s.</th>
<th>Reg2 v.s.</th>
<th>RegR v.s.</th>
<th>Neg v.s.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td>Reg2</td>
<td>RegR</td>
<td>Neg</td>
<td>Part</td>
</tr>
<tr>
<td>Panel Tobit: $y_{it}^* = a_0 + \delta d_i + \rho y_{it-1}^* + \delta(\tilde{y}<em>{it-1}^* - y</em>{it-1}^*) + \phi_1(1/t) + e_{it}$, $d_i = 0$ if treated</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}$</td>
<td>-0.05</td>
<td>0.17</td>
<td>0.31</td>
<td>0.05</td>
</tr>
<tr>
<td>Panel Tobit: $y_{it}^* = a_0 + \delta d_i + \rho y_{it-1}^* + \delta(\tilde{y}<em>{it-1}^* - y</em>{it-1}^*) + \phi_2 t + e_{it}$, $d_i = 0$ if treated</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}$</td>
<td>-0.05</td>
<td>0.18</td>
<td>0.33</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Too Less reject. 3 out of 8 (=40%) fail to reject.
Table 3: Dynamic Tobit and Panel Regressions with Random Effects

<table>
<thead>
<tr>
<th>Controlled Treated</th>
<th>Reg1 v.s. Reg2</th>
<th>Reg1 v.s. RegR</th>
<th>Reg1 v.s. Neg</th>
<th>Reg1 v.s. Part</th>
<th>Reg2 v.s. RegR</th>
<th>Reg2 v.s. Neg</th>
<th>Reg2 v.s. Part</th>
<th>RegR v.s. Neg</th>
<th>RegR v.s. Part</th>
<th>Neg v.s. Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel Tobit: ( y_{it}^* = a_0 + \delta d_i + \rho y_{it-1}^* + \delta (\tilde{y}<em>{it-1}^* - y</em>{it-1}^*) + \phi_1 (1/t) + e_{it}, d_i = 0 \text{ if treated} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\delta} )</td>
<td>-0.05</td>
<td>0.17</td>
<td>0.31</td>
<td>0.05</td>
<td>0.21</td>
<td>0.34</td>
<td>0.10</td>
<td>0.11</td>
<td>-0.11</td>
<td>-0.22</td>
</tr>
<tr>
<td>Can’t interpret as no treatment effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel Tobit: \( y_{it}^* = a_0 + \delta d_i + \rho y_{it-1}^* + \delta (\tilde{y}_{it-1}^* - y_{it-1}^*) + \phi_2 t + e_{it}, d_i = 0 \text{ if treated} \)

| \( \hat{\delta} \) | -0.05 | 0.18 | 0.33 | 0.06 | 0.23 | 0.38 | 0.11 | 0.12 | -0.12 | -0.25 |
Dynamic Censored Regressions

Table 3: Dynamic Tobit and Panel Regressions with Random Effects

<table>
<thead>
<tr>
<th>Controlled</th>
<th>Reg1 v.s.</th>
<th>Reg2 v.s.</th>
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<tbody>
<tr>
<td>Treated</td>
<td>Reg2</td>
<td>RegR</td>
<td>Neg</td>
<td>Part</td>
</tr>
<tr>
<td></td>
<td>RegR</td>
<td>Neg</td>
<td>Part</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Neg</td>
<td>Part</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Part</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Choice of deterministic series does matter. Which one is correct then?

Panel Tobit: \( y_{it}^* = a_0 + \delta d_i + \rho y_{it-1}^* + \delta(\tilde{y}_{it-1} - y_{it-1}^*) + \phi t + e_{it}, d_i = 0 \) if treated

<table>
<thead>
<tr>
<th>( \hat{\delta} )</th>
<th>0.36</th>
<th>0.42</th>
<th>0.51</th>
<th>0.50</th>
<th>0.27</th>
<th>0.36</th>
<th>0.40</th>
<th>0.56</th>
<th>0.54</th>
<th>0.78</th>
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<tbody>
<tr>
<td>( \hat{\phi} )</td>
<td>-0.05</td>
<td>0.18</td>
<td>0.33</td>
<td>0.06</td>
<td>0.23</td>
<td>0.38</td>
<td>0.11</td>
<td>0.12</td>
<td>-0.12</td>
<td>-0.25</td>
</tr>
<tr>
<td>( \hat{\delta} )</td>
<td>0.29</td>
<td>0.38</td>
<td>0.44</td>
<td>0.43</td>
<td>0.19</td>
<td>0.24</td>
<td>0.26</td>
<td>0.45</td>
<td>0.42</td>
<td>0.62</td>
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</table>
## MWW, Dynamic Censored, Eyeball Tests

<table>
<thead>
<tr>
<th>Controlled</th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Neg</th>
<th>Part</th>
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</thead>
<tbody>
<tr>
<td>Eye Ball</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>MWW</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Censored</td>
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<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
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</tbody>
</table>
## MWW, Dynamic Censored, Eyeball Tests

<table>
<thead>
<tr>
<th></th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Reg2 v.s.</th>
<th>RegR</th>
<th>Neg</th>
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<th>RegR v.s.</th>
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<td><strong>Controlled</strong></td>
<td></td>
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<td><strong>Censored</strong></td>
<td>No</td>
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<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

There is no “No” case!
Fragile and Disappointed!
Approximating Decay Function

Regular 1 game
Approximating Decay Function

Fitted Well!
How did I do that?
Approximating Decay Function

Simple Exponential Decay Model for transitional path

\[ E(y_{it} | a_i, y_{i1}) = a_i + (y_{i1} - a_i)e^{-\beta(t-1)} \]
Approximating Decay Function

Simple Exponential Decay Model for transitional path

\[ E(y_{it} | a_i, y_{i1}) = a_i + (y_{i1} - a_i) e^{-\beta(t-1)} \]

Stead state value: A subject outcome converges to this value

Initial outcome

Exponential Decay
Approximating Decay Function

Simple Exponential Decay Model for transitional path

\[
E(y_{it} | a_i, y_{i1}) = a_i + (y_{i1} - a_i) e^{-\beta(t-1)}
\]

\[
E(y_{it} | a_i, y_{i0}) = a_i(1 - e^{-\beta}) + \{a_i + (y_{i1} - a_i)e^{-\beta(t-2)}\} e^{-\beta}
\]

\[
E(y_{it} | a_i, y_{i0}) = a_i(1 - e^{-\beta}) + e^{-\beta}E(y_{it-1} | a_i, y_{i1})
\]

\[
E(y_{it} | a_i, y_{i1}) = a_i(1 - \rho) + \rho E(y_{it-1} | a_i, y_{i1})
\]

AR(1) Structure: Expected outcomes.
Approximating Decay Function

Simple Exponential Decay Model for transitional path

\[
E(y_{it} | a_i, y_{i1}) = a_i + (y_{i1} - a_i)e^{-\beta(t-1)}
\]

\[
E(y_{it} | a_i, y_{i0}) = a_i(1 - e^{-\beta}) + \left\{ a_i + (y_{i1} - a_i)e^{-\beta(t-2)} \right\} e^{-\beta}
\]

\[
= a_i(1 - e^{-\beta}) + e^{-\beta}E(y_{it-1} | a_i, y_{i1})
\]

\[
E(y_{it} | a_i, y_{i1}) = a_i(1 - \rho) + \rho E(y_{it-1} | a_i, y_{i1})
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AR(1) Structure: Expected outcomes.
Approximating Decay Function

Simple Exponential Decay Model for transitional path

\[
E(y_{it} \mid a_i, y_{i1}) = a_i + (y_{i1} - a_i)e^{-\beta(t-1)}
\]
\[
E(y_{it} \mid a_i, y_{i0}) = \left\{ a_i + (y_{i1} - a_i)e^{-\beta(t-2)} \right\} e^{-\beta} + a_i(1 - e^{-\beta})
\]
\[
= a_i(1 - e^{-\beta}) + e^{-\beta}E(y_{it-1} \mid a_i, y_{i1})
\]
\[
E(y_{it} \mid a_i, y_{i1}) = a_i(1 - \rho) + \rho E(y_{it-1} \mid a_i, y_{i1})
\]

AR(1) Structure: Expected outcomes.

Next, introduce expectation errors

\[
u_{it} = y_{it} - E(y_{it} \mid a_i, y_{i1}) = a_i + (y_{i1} - a_i)\rho^{t-1},
\]
\[
u_{i1} = y_{i1} - E(y_{i1} \mid a_i).
\]
Approximating Decay Function

Rewrite the model

\[ y_{it} = a_i + \lambda_i \rho^{t-1} + u_{it}, \quad u_{it} = \phi u_{i{t-1}} + \zeta_{it}. \]

\[ \lambda_i = y_{i1} - a_i. \]

\[ \phi = 0 \iff \text{the rational expectation} \]
\[ \phi \neq 0 \iff \text{the irrational expectation} \]

\[ \rho^{t-1} = \text{Common Factor}. \]
\[ \lambda_i = \text{Factor loadings: Economic distance between common factor and } y_{it} \]

Common factor structure: Popular in Finance.
Cross section dependence does matter

Key: When \( t=1 \), No cross sectional dependence:
    Obvious since subjects are selected randomly.
When \( t>1 \), outcomes are cross sectionally dependent
    why? From learning!!!!
Approximating Decay Function

Rewrite the model

\[ y_{it} = a_i + \lambda_i \rho^{t-1} + u_{it}, \quad u_{it} = \phi u_{it-1} + \xi_{it}. \]

\[ \lambda_i = y_{it} - a_i. \]

\[ \phi = 0 \iff \text{the rational expectation} \]

\[ \phi \neq 0 \iff \text{the irrational expectation} \]

\[ \rho^{t-1} = \text{Common Factor.} \]

\[ \lambda_i = \text{Factor loadings: Economic distance between common factor and } y_{it} \]

Common factor structure: Popular in Finance.

Cross section dependence does matter

Key: When \( t=1 \), No cross sectional dependence:

Obvious since subjects are selected randomly.

When \( t \geq 1 \), outcomes are cross sectionally dependent

Why? From learning!!!!
Approximating Decay Function

Rewrite the model

\[ y_{it} = a_i + \lambda_i \rho^{t-1} + u_{it}, \quad u_{it} = \phi u_{it-1} + \zeta_{it}. \]
\[ \lambda_i = y_{i1} - a_i. \]
\[ \phi = 0 \Leftrightarrow \text{the rational expectation} \]
\[ \phi \neq 0 \Leftrightarrow \text{the irrational expectation} \]

\[ \rho^{t-1} = \text{Common Factor}. \]
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Approximating Decay Function

Rewrite the model

\[ y_{it} = a_i + \lambda_i \rho^{t-1} + u_{it}, \quad u_{it} = \phi u_{it-1} + \zeta_{it}. \]
\[ \lambda_i = y_{i1} - a_i. \]
\[ \phi = 0 \iff \text{the rational expectation} \]
\[ \phi \neq 0 \iff \text{the irrational expectation} \]

Inconsistent Panel AR(1) Model

\[ y_{it} - \rho y_{it-1} = a_i (1 - \rho) + u_{it} - \rho u_{it-1}. \]
\[ y_{it} = a_i (1 - \rho) + \rho y_{it-1} + e_{it}, \quad \text{for} \ e_{it} = u_{it} - \rho u_{it-1}. \]
\[ E(y_{it-1} e_{it}) = E(y_{it-1} u_{it-1}) \neq 0. \quad \text{Inconsistent.} \]
How to Estimate Treatment Effects

Take Cross Sectional Averages for each round.

\[ y_t = \bar{a} + \mu \rho^{t-1} + u_t \]

Set \( \bar{a} = 0 \)

If the outcome of the dominant strategy = 0.

Now define the overall treatment effects as

\[ TE = \text{plim}_{N \to \infty} \left[ \frac{1}{N_c} \sum_{i=1}^{N_c} \sum_{t=1}^{T} y_{c,it} - \frac{1}{N_\tau} \sum_{i=1}^{N_\tau} \sum_{t=1}^{T} y_{\tau,it} \right] \]

\[ = \mu_c \frac{1 - \rho^T_c}{1 - \rho_c} - \mu_\tau \frac{1 - \rho^T_\tau}{1 - \rho_\tau}, \]

Which depends on T.
How to Estimate Treatment Effects

Consider two experimental outcomes A & B
How to Estimate Treatment Effects

Total Contribution in A = Yellow Area

\[ \frac{1}{N_A} \sum_{i=1}^{N_A} \sum_{t=1}^{T} y_{A,it} = \mu_A \frac{1 - \rho_A^T}{1 - \rho_A} \]
How to Estimate Treatment Effects

Total Contribution in $B = \text{Green Area}$

$$\frac{1}{N_B} \sum_{i=1}^{N_B} \sum_{t=1}^{T} y_{B, it} = \mu_B \frac{1 - \rho_B^T}{1 - \rho_B}$$
How to Estimate Treatment Effects

Suppose that they are same

\[
\mu_A \frac{1 - \rho_A^T}{1 - \rho_A} = \mu_B \frac{1 - \rho_B^T}{1 - \rho_B}
\]
How to Estimate Treatment Effects

Now increase one more round

Contribution

Rounds
Now increase one more round

=> Contribution in B > Contribution in A

\[ \mu_A \frac{1 - \rho_A^{T+1}}{1 - \rho_A} < \mu_B \frac{1 - \rho_B^{T+1}}{1 - \rho_B} \]
How to Estimate Treatment Effects

Define Asymptotic Treatment Effect as

\[
\text{Asy. TE} = \Pi = \lim_{T \to \infty} \frac{\mu_c}{1 - \rho_c} - \frac{\mu_\tau}{1 - \rho_\tau} = \Pi_c - \Pi_\tau
\]

- Robust: Does not dependent on the number of Rounds!
How to Estimate Treatment Effects

Define Asymptotic Treatment Effect as

\[ \text{Asy. TE} = \Pi = \lim_{T \to \infty} \frac{\mu_c}{1 - \rho_c} - \frac{\mu_\tau}{1 - \rho_\tau} = \Pi_c - \Pi_\tau \]

How to estimate them?
Run the following trend regression

\[ \log \bar{y}_{st} = \log \mu_s + (\log \rho_s)(t - 1) + \nu_{st}; \quad t = 1, \ldots, T \]

\[ \bar{y}_{st} = \frac{1}{N} \sum_{i=1}^{N} y_{s,it} \]

Then take exponential and get

\[ \hat{\Pi} = \frac{\hat{\mu}_c}{1 - \hat{\rho}_c} - \frac{\hat{\mu}_\tau}{1 - \hat{\rho}_\tau} \]
How to Estimate Treatment Effects

Simple Regression:
Trend Regression with logged cross sectional averages

\[
\log \bar{y}_{st} = \log \mu_s + (\log \rho_s)(t - 1) + \nu_{st}
\]

Then Estimate the following Asymptotic Treatment Effects

\[
\hat{\Pi} = \frac{\hat{\mu}_c}{1 - \hat{\rho}_c} - \frac{\hat{\mu}_\tau}{1 - \hat{\rho}_\tau}
\]

• See eq. (27) in the paper how to calculate the sample variance of Asy. TE.
• See Appendix C for sample STATA Code
• See Section 4 in the paper for detailed asymptotic (econometric) properties of the suggested estimators and tests
How to Estimate Treatment Effects

\[
\log \bar{y}_{st} = \log \mu_s + (\log \rho_s)(t - 1) + \nu_{st}; \quad t = 1, \ldots, T
\]
\[
\bar{y}_{st} = \frac{1}{N} \sum_{i=1}^{N} y_{s,it}
\]

Works only when all subjects’ dominant strategy = Nash.

How to test if it is true?

\[
\log(\bar{y}_{st} - \delta_{sj}) = \alpha_0 + \gamma(t - 1) + \nu_{s,jt}^*
\]

Choose various values of \( \delta_{sj} \) and minimize SSE with respect to \( \delta_{sj} \)

If \( \delta_{s}^* = 0 \), then overall convergence occurs!

Table 4: Empirical Results based on Trend Regressions

<table>
<thead>
<tr>
<th>Experiments</th>
<th>$\hat{\delta}_s$</th>
<th>$\hat{\alpha}_s$(s.d)</th>
<th>$\hat{\gamma}_s$(s.d)</th>
<th>$\hat{\mu}_s$(s.d)</th>
<th>$\hat{\rho}_s$(s.d)</th>
<th>$\hat{\Pi}_s$(s.d)</th>
<th>1% Life</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reg1</td>
<td>0</td>
<td>-0.600</td>
<td>-0.081</td>
<td>0.549</td>
<td>0.922</td>
<td>7.070</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.032)</td>
<td>(0.006)</td>
<td>(0.017)</td>
<td>(0.005)</td>
<td>(0.529)</td>
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<tr>
<td>Reg2</td>
<td>0</td>
<td>-0.558</td>
<td>-0.078</td>
<td>0.572</td>
<td>0.925</td>
<td>7.641</td>
<td>59</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.061)</td>
<td>(0.011)</td>
<td>(0.034)</td>
<td>(0.010)</td>
<td>(1.130)</td>
<td></td>
</tr>
<tr>
<td>RegR</td>
<td>0</td>
<td>-0.705</td>
<td>-0.214</td>
<td>0.494</td>
<td>0.807</td>
<td>2.561</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.076)</td>
<td>(0.014)</td>
<td>(0.035)</td>
<td>(0.011)</td>
<td>(0.237)</td>
<td></td>
</tr>
<tr>
<td>Neg$^1$</td>
<td>0</td>
<td>-1.369</td>
<td>-0.097</td>
<td>0.255</td>
<td>0.912</td>
<td>2.898</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.053)</td>
<td>(0.011)</td>
<td>(0.014)</td>
<td>(0.010)</td>
<td>(0.312)</td>
<td></td>
</tr>
<tr>
<td>Part</td>
<td>0</td>
<td>-0.605</td>
<td>-0.126</td>
<td>0.546</td>
<td>0.881</td>
<td>4.608</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.115)</td>
<td>(0.022)</td>
<td>(0.057)</td>
<td>(0.017)</td>
<td>(0.836)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The numbers in parentheses are standard errors based on Andrews' HAC estimation.

1) The samples in the last round are not used since its cross sectional average is near to zero.
Table 5: Estimation and Testing of Treatment Effects

<table>
<thead>
<tr>
<th>Controlled</th>
<th>Treated</th>
<th>$\hat{\alpha}<em>c - \hat{\alpha}</em>\tau$</th>
<th>t-ratio</th>
<th>$\hat{\gamma}<em>c - \hat{\gamma}</em>\tau$</th>
<th>t-ratio</th>
<th>$\hat{\Pi}$</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reg1</td>
<td>Reg2</td>
<td>-0.042</td>
<td>-0.615</td>
<td>-0.003</td>
<td>-0.226</td>
<td>-0.570</td>
<td>-0.457</td>
</tr>
<tr>
<td></td>
<td>RegR</td>
<td>0.105</td>
<td>1.274</td>
<td>0.133</td>
<td>8.639</td>
<td>4.509</td>
<td>8.332</td>
</tr>
<tr>
<td></td>
<td>Neg</td>
<td>0.431</td>
<td>1.115</td>
<td>0.143</td>
<td>1.976</td>
<td>4.172</td>
<td>4.961</td>
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<tr>
<td></td>
<td>Part</td>
<td>0.004</td>
<td>0.037</td>
<td>0.045</td>
<td>2.036</td>
<td>2.462</td>
<td>2.684</td>
</tr>
<tr>
<td>Reg2</td>
<td>RegR</td>
<td>0.147</td>
<td>1.515</td>
<td>0.136</td>
<td>7.487</td>
<td>5.080</td>
<td>4.618</td>
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<tr>
<td></td>
<td>Neg</td>
<td>0.473</td>
<td>1.214</td>
<td>0.146</td>
<td>1.999</td>
<td>4.743</td>
<td>3.289</td>
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<tr>
<td></td>
<td>Part</td>
<td>0.047</td>
<td>0.359</td>
<td>0.048</td>
<td>1.989</td>
<td>3.033</td>
<td>2.287</td>
</tr>
<tr>
<td>RegR</td>
<td>Neg</td>
<td>0.326</td>
<td>0.830</td>
<td>0.009</td>
<td>0.129</td>
<td>-0.337</td>
<td>-0.614</td>
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<tr>
<td></td>
<td>Part</td>
<td>-0.101</td>
<td>-0.732</td>
<td>-0.088</td>
<td>-3.421</td>
<td>-2.047</td>
<td>-2.631</td>
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<tr>
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<td>Neg</td>
<td>-0.427</td>
<td>-1.062</td>
<td>-0.098</td>
<td>-1.297</td>
<td>-2.829</td>
<td>-2.946</td>
</tr>
</tbody>
</table>

Note: Andrews’ HAC estimator is used for the estimation of the long run variance.
## Final Results

<table>
<thead>
<tr>
<th>Controlled Treated</th>
<th>Reg2</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>Reg2 v.s.</th>
<th>RegR</th>
<th>Neg</th>
<th>Part</th>
<th>RegR v.s.</th>
<th>Neg</th>
<th>Part</th>
<th>Neg v.s.</th>
<th>Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eye Ball</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>MWW</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Censored</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Sul’s T-Reg</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>
Monte Carlo Studies

• See Section 6 in the paper.
• Major Findings
  – The proposed estimators and tests work well.
  – Don’t need a large T (or round) to improve the power of the test. (Reason: If subject’s outcomes are closed to zero, not helpful for the estimation and test)
  – T=10 seems to be fine. Larger N (total number of subjects) is much more helpful for sharpening up the statistical inference.
Conclusion and Extension

• Show that existent estimators are inappropriate to measure treatment effects
• Suggest a simple but efficient estimation method
• Works well in practice. Verify Andreoni’s findings
• Key Requirement: Experimental outcomes should converge. Otherwise, use alternative method (in progress, Kong and Sul, 2012)
Conclusion and Extension

• Ready to read the paper?
• Comments welcomed!
• Send your valuable comments to d.sul@utdallas.edu
IWW (1994), MPCR = 0.3, Group Size = 40, Cash Incentive

Divergence Case: May exist several sub-convergent clubs

Overall Average

Rounds
IWW (1994), MPCR = 0.3, Group Size = 40, Cash Incentive

Results: At least three clubs. One Nash, Pareto and confused clubs.
Preview of Kong & Sul’s Convergent Test

Will be available soon!
(Lease date: Fall, 2012)