How to Apply EBT Data on WIC-related Research? New Concepts and New Approaches

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Disclaimer: The views and opinions expressed are those of the investigators and do not reflect the position or policy of the funding agencies, including the USDA, NIH, and any funding or participating companies. Results are preliminary.
A Topic for More General Audience

Source: Dreamworks Inc.
EBT Data is One Part of Multi-dimensional MIS Data

Individual & Household Level
Vendor Level
UPC Level

Socio-Demo

EBT

Health

Clinic

Individual & Household Level

Individual Level

Clinic Level
EBT Data is the Tip of Iceberg...

- Interactions between
  - Participants
    - Individual & Family
  - Staff
  - Vendors
- Hard Environment
  - e.g. physical
- Soft Environment
  - E.g. policy & regulation

Source: Iceberg Dragon by Johanna Tarkela (2017)
How to Train Your EBT Data?

Source: IBM
Benefit Prescribing Patterns

- What’s the usual day of a month to start a benefit cycle?
  - What’s the usual day of a month to end a benefit cycle?
- Answer: Every day is possible 😊
- How about repetition?
- Virginia EBT data in May 2014~April 2016
- Households with completed benefit instruments and demographics: 181,233
  - But not every household has the same package all the time (e.g. formula stops after 1\textsuperscript{st} birthday)
Prescription Patterns of CVV

- Households with CVV benefits: 176,440
- “One Shot” households (only one benefit cycle): 11,231
- Households with repeated CVV benefits: 165,209
- How about their starting and ending days of the month?
# of Unique Starting and Ending Days

### # of Unique Starting Days

- **1 day**: 22%
- **2 days**: 13%
- **3 days**: 21%
- **4 days**: 15%
- **5+ days**: 8%

### # of Unique Ending Days

- **1 day**: 92%
- **2+ days**: 8%
Gap Days

Stable ending days, varying starting days

Gap = # of days between last ending day and the next starting day

E.g. previous benefit ended on 3/15, but next benefit started on 3/30, then the gap is 15 days
Distribution of Total Gap Days in A Year

\[ g(y) = \frac{1}{\sigma^2} \frac{\frac{1}{y\sigma^2} e^{-\frac{y}{(\sigma^2\mu)}}}{\Gamma\left(\frac{1}{\sigma^2}\right)} \quad \text{for} \quad y > 0 \]
Application: Dropout before 1st B-Day

- Dropout:
  - No active WIC benefit redemption or participation activities for 3 months since last benefit ending date

- What’s the predictor of dropout before 1st Birthday?
  - Breastfeeding status?
  - Number of participants in the households?
  - Race/ethnicity?
  - Mom’s age?

- Here’s the answer based on binary analyses
Dropout Before 1\textsuperscript{st} B-Day by Breastfeeding Status

<table>
<thead>
<tr>
<th></th>
<th>Full BF</th>
<th>Partial BF</th>
<th>Full Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dropout %</td>
<td>32.7</td>
<td>25.1</td>
<td>29.1</td>
</tr>
</tbody>
</table>

P<0.001
Dropout Before 1st B-Day by # of Participants in the Households

Dropout %

- N=2: 27.6%
- N=3: 36.8%
- N>=4: 36.6%

P<0.001
Dropout Before 1\textsuperscript{st} B-Day by Race/Ethnicity

- Non-H White: 30.4
- Non-H Black: 30.5
- Hispanics: 24.4
- Other: 30.4

Statistical Significance: P<0.001
Dropout Before 1st B-Day by Mom’s Age

P<0.001
Multivariate Analyses

- Logistic Regression
- Two more predictors
- Total days: total active WIC benefit days
- Gap days: total gap days from the participation
- Odds Ratio (OR):
  - If it’s greater than 1, more likely to dropout
  - If it’s smaller than 1, less likely to dropout
## Results

<table>
<thead>
<tr>
<th>Predictors</th>
<th>OR</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Days</td>
<td>0.973</td>
<td>0.972 - 0.974</td>
</tr>
<tr>
<td>Gap Days</td>
<td>1.012</td>
<td>1.010 - 1.015</td>
</tr>
<tr>
<td>Mom’s age &lt;=300m</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>300m, 360m</td>
<td>0.850</td>
<td>0.707 - 1.021</td>
</tr>
<tr>
<td>360m, 420m</td>
<td>0.880</td>
<td>0.710 - 1.088</td>
</tr>
<tr>
<td>&gt;420m</td>
<td>0.742</td>
<td>0.575 - 0.953</td>
</tr>
<tr>
<td>Full Formula</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>Fully Breastfeed</td>
<td>0.992</td>
<td>0.811 - 1.211</td>
</tr>
<tr>
<td>Partial Breastfeed</td>
<td>0.890</td>
<td>0.727 - 1.087</td>
</tr>
<tr>
<td>N=2</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>N=3</td>
<td>1.097</td>
<td>0.881 - 1.364</td>
</tr>
<tr>
<td>N&gt;=4</td>
<td>0.929</td>
<td>0.475 - 1.778</td>
</tr>
</tbody>
</table>

*Other variables controlled: race/ethnicity, language spoken at home, infant gender*
The Hidden World has Gold Mines

Source: Dreamworks Inc.
Working Paper on CVV Redemption

- **Background**
- CVV EBT System
- WIC: Authorized Product List (APL)
- Retailers:
  - Universal Product Code (UPC) (12-digit bar code)
  - Price Look-up Code (PLU) (4- or 5-digit code)
- EBT: Mapping APL with UPC or PLU
- If not successful, denied redemption
  - Wrongful denial => frustration
Mapping Policy

- Full mapping
  - Strict one-to-one mapping between APL and UPC/PLU
- Partial mapping
  - Allow many-to-one mapping between APL and UPC/PLU
- “Generic code” designated by USDA/FNS
  - “4469, 44691”: code for any produce
Vendor Variations

- After EBT adoption in Virginia in May 2014, optional on full mapping or partial mapping
- Vendor variations
- Full mapping stores
  - No generic code redemption at all
- Full mapping stores that allow generic codes
  - Cashiers can enter generic codes occasionally to process
- Partial mapping stores
  - All CVV redemptions with generic codes
Methods

- Virginia EBT data in 2015
- Outcome: Mean Monthly CVV Redemption Rate
- Participants’ information
  - Race/ethnicity (Non-H White/Non-H Black/Hispanic, Others)
  - Number of WIC participants (1, 2, ≥3)
- Vendor Information
  - Urban or rural
  - Vendor size (Large, ≥10 registers; Medium plus, 5–9 registers with annual revenue ≥$100k; Medium, 5–9 registers with annual revenue <$100k; Small, 1–4 registers)
Generic Code Rate (GCR)

- Vendor GCR

Total CVV Transaction = $1,000
Generic Code Transaction = $100

Vendor GCR = $100/($900+$100) = 10%
Vendor’s Generic Code Rate

Full Mapping Store

0 ≤ GCR < 100%

Partial Mapping Store

GCR = 100%
Distribution of Full vs. Partial Mapping Vendors (N=849)

**Urban Vendors (N=623)**
- Full Mapping, 73.7%
- Partial Mapping, 26.3%
- Mean GCR=31.9%

**Rural Vendors (N=226)**
- Full Mapping, 88.9%
- Partial Mapping, 11.1%
- Mean GCR=13.4%
Distribution of Full vs. Partial Mapping Vendors (N=849)

Large Vendors (N=308)
Mean GCR=47.7%

Small Vendors (N=73)
Mean GCR=49.6%
Distribution of Full vs. Partial Mapping Vendors (N=849)

Medium Plus Vendors (N=188)
- Full Mapping: 96.8%
- Partial Mapping: 3.2%

Mean GCR=8.2%

Medium Vendors (N=280)
- Full Mapping: 93.2%
- Partial Mapping: 6.8%

Mean GCR=10.8%
Generic Code Rate (GCR)

- Household GCR

  - Full Mapping Store
    - CVV redeemed $10
    - GCR = $9 / ($10 + $9)
    - GCR = 47.4%

  - Partial Mapping Store
    - CVV redeemed $9
Partial Mapping Vendor Rate

- One household can visit multiple vendors
  - Some vendors are full mapping stores
  - Some vendors are partial mapping stores
- Partial mapping vendor rate (PMVR) =
  - \( \frac{\text{# of partial mapping vendors visited}}{\text{Total # of vendors visited}} \)
  - E.g. 5 stores visited: 2 PM, 3 FM, PMVR=2/5=40%
  - Higher partial mapping vendor rate indicates more exposure to partial mapping
Most Visited Vendor

- Urban vs. rural
  - E.g. visits in urban stores 9 times but in rural stores 2 times
  - Most visited vendor type is urban

- Large vs. medium plus vs. medium vs. small
  - E.g. visits in large stores (2 times), medium plus stores (2 times), medium stores (1 times), and small stores (5 times)
  - Most visited vendor type is small
Generalized Linear Regression Model

- **Outcome:** Mean Monthly CVV Redemption Rates
- **Explanatory Variables:**
  - Partial Mapping Vendor Rate
  - Most visited vendor type (urban/rural)
  - Most visited vendor type (large/medium+/medium/small)
  - Race/ethnicity
  - # of participants
## Results: Participant Factors

<table>
<thead>
<tr>
<th>Race/Ethnicity</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
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<tr>
<td>N-H White</td>
<td>Reference Group</td>
<td></td>
</tr>
<tr>
<td>N-H Black</td>
<td>-0.026</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.048</td>
<td>&lt;0.01</td>
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<tr>
<td>Others</td>
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<tr>
<td># of Participants</td>
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<td></td>
</tr>
<tr>
<td>1 Reference Group</td>
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<tr>
<td>2</td>
<td>-0.026</td>
<td>&lt;0.01</td>
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<tr>
<td>≥3</td>
<td>-0.019</td>
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<td>Rural Reference Group</td>
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<td>Medium plus</td>
<td>-0.001</td>
<td>&gt;0.05</td>
</tr>
<tr>
<td>Medium</td>
<td>-0.004</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Small</td>
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<td>&lt;0.01</td>
</tr>
<tr>
<td>Large Reference Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium plus</td>
<td>-0.001</td>
<td>&gt;0.05</td>
</tr>
<tr>
<td>Medium</td>
<td>-0.004</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Small</td>
<td>-0.022</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Partial Mapping Vendor Rate</td>
<td>-0.002</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

More exposure to Partial Mapping Vendors, lower CVV Redemption Rate
### Households in Urban Area

<table>
<thead>
<tr>
<th>Model 1 Most Visited Vendor is Large</th>
<th>Model 2 Most Visited Vendor is Medium Plus</th>
<th>Model 3 Most Visited Vendor is Medium</th>
<th>Model 4 Most Visited Vendor is Small</th>
</tr>
</thead>
<tbody>
<tr>
<td>PMVR</td>
<td>-0.104</td>
<td>0.147</td>
<td>0.197</td>
</tr>
<tr>
<td>P-Value</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
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</tbody>
</table>

More exposure to partial mapping stores increases the redemption rate, except in large vendor group.
Adventure to Hidden World Continues

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Most Visited Vendor is Large</td>
<td>Most Visited Vendor is Medium Plus</td>
<td>Most Visited Vendor is Medium</td>
<td>Most Visited Vendor is Small</td>
</tr>
<tr>
<td>PMVR</td>
<td>-0.236</td>
<td>-0.209</td>
<td>1.039</td>
<td>-0.361</td>
</tr>
<tr>
<td>P-Value</td>
<td>&gt;0.05</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

More exposure to partial mapping stores decreases the redemption rate except in medium store.

Partial mapping stores can be different between urban and rural areas.
More Adventures in Hidden World
How to Train Your Dragon?
The Sky is the Limit

Source: Steamcommunity.com
Credits to All

- **USDA:** Patrick McLaughlin, Joanne Guthrie, Xinzhe Cheng
- **Old Dominion University:** Chunayi Tang, Yuzhong Shen, Junzhou Zhang, Kayoung Park
- **Virginia Department of Health:** Paula Garrett, Vanitha Padma, Melanie Barthlow, Todd Osborne, Brian Tun et al.
- **Virginia WIC Clinic Coordinators and all their WONDERFUL Staff**
- **More WIC State Agencies:** Dave Thomason (KS), Denise Ferris (WV)
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