

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

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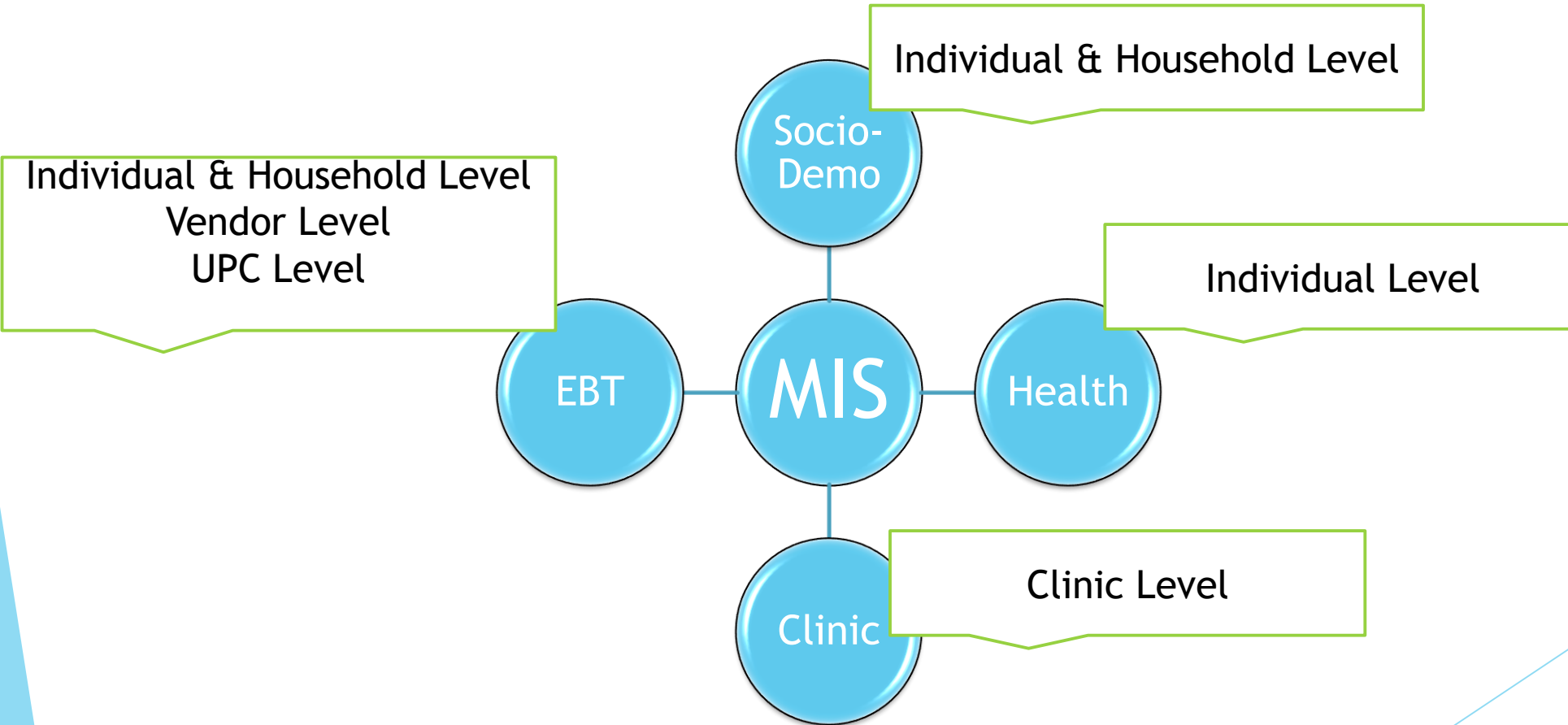
Disclaimer: The views and opinions expressed are those of the investigators and do not reflect the position or policy of the funding agencies, including the USDA, NIH, and any funding or participating companies. Results are preliminary.

# A Topic for More General Audience



Source: Dreamworks Inc.

# EBT Data is One Part of Multi-dimensional MIS Data



# 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

# How to Train Your EBT Data?



Source: IBM

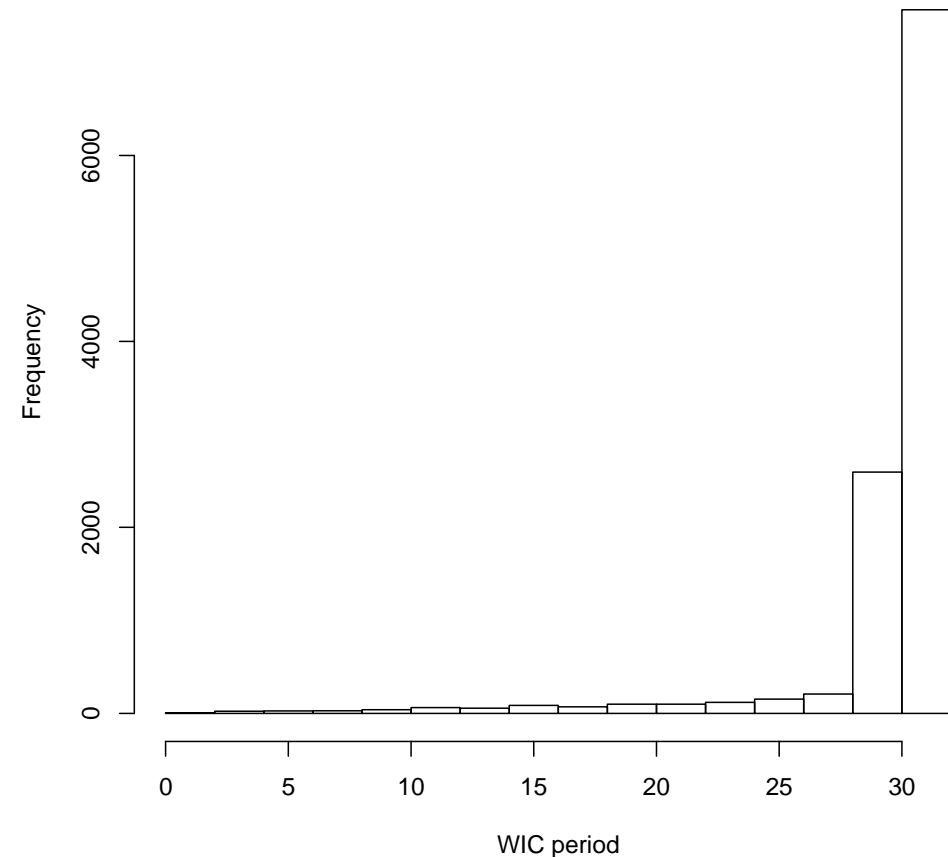
# Benefit Prescribing Patterns

- ▶ 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<sup>st</sup> birthday)

# Prescription Patterns of CVV

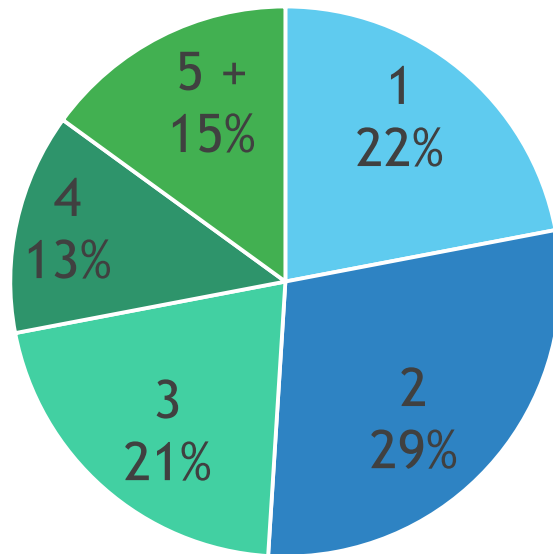
- ▶ Households with CVV benefits: 176,440
- ▶ “One Shot” households (only one benefit cycle): 11,231
- ▶ Households with repeated CVV benefits: 165,209
- ▶ How about their starting and ending days of the month?

Histogram of WIC period (one shot families)



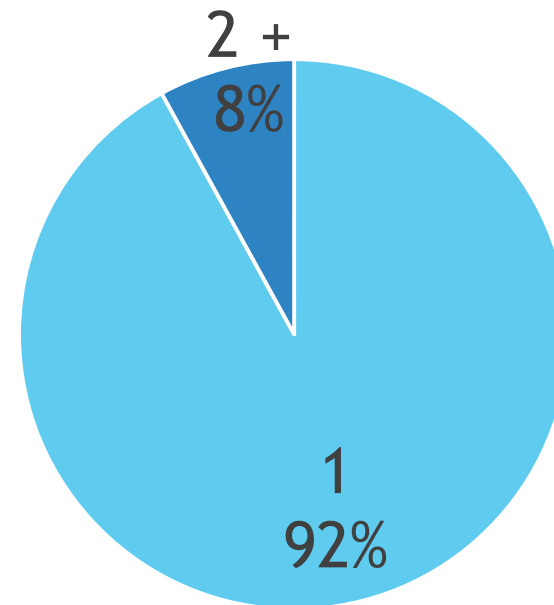
# # of Unique Starting and Ending Days

# of Unique Starting Days



■ 1 ■ 2 ■ 3 ■ 4 ■ 5 +

# of Unique Ending Days



■ 1 ■ 2 +



# Gap Days



Stable ending days, varying starting days

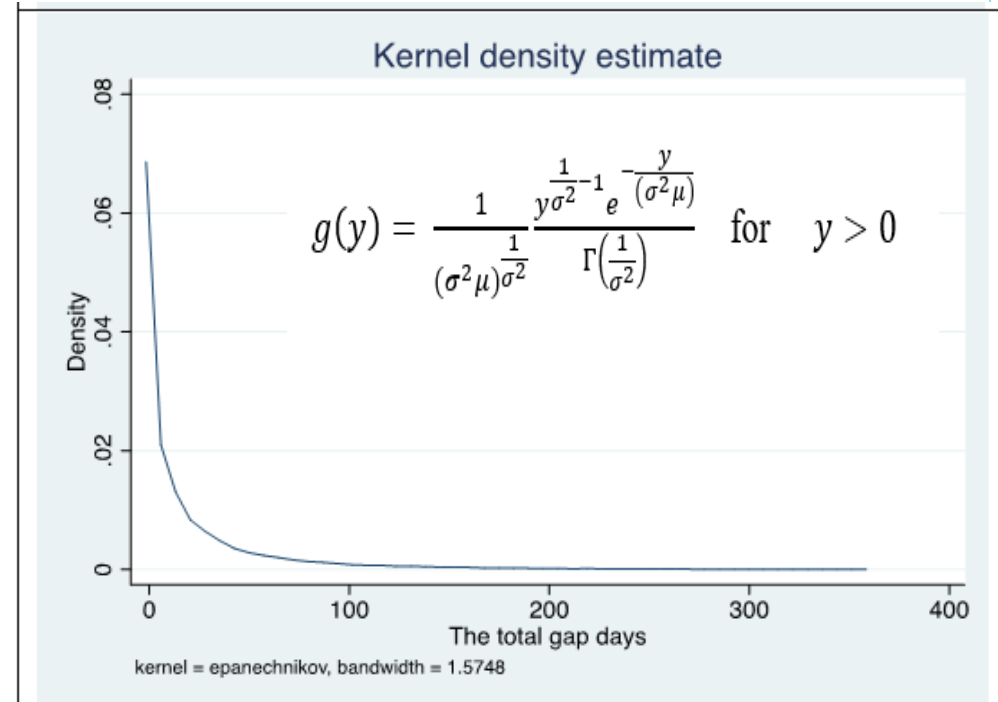
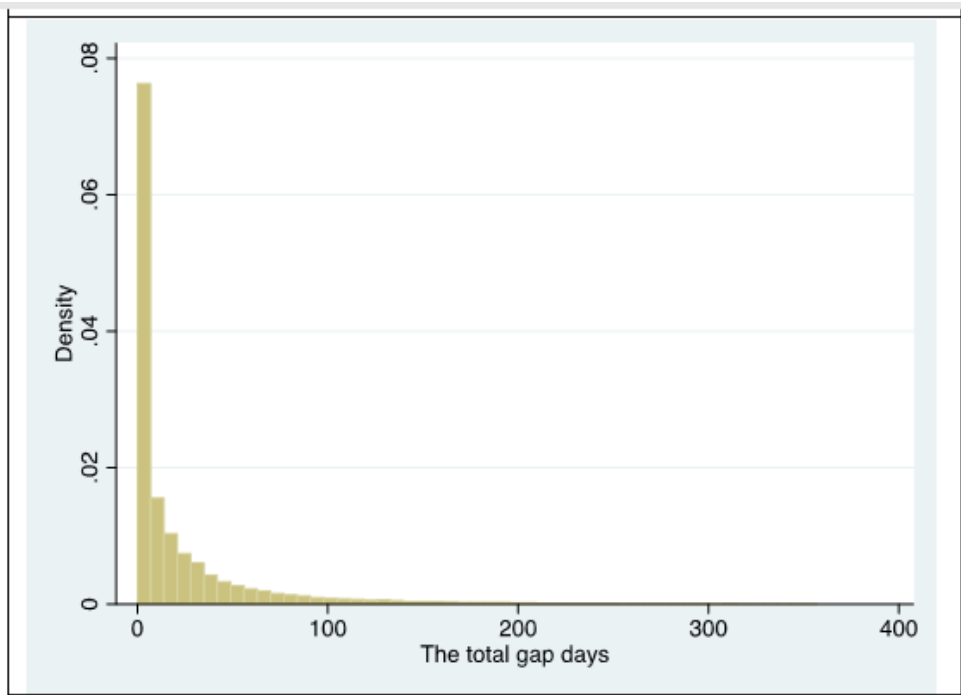


Gap = # of days between last ending day and the next starting day



E.g. previous benefit ended on 3/15, but next benefit started on 3/30, then the gap is 15 days

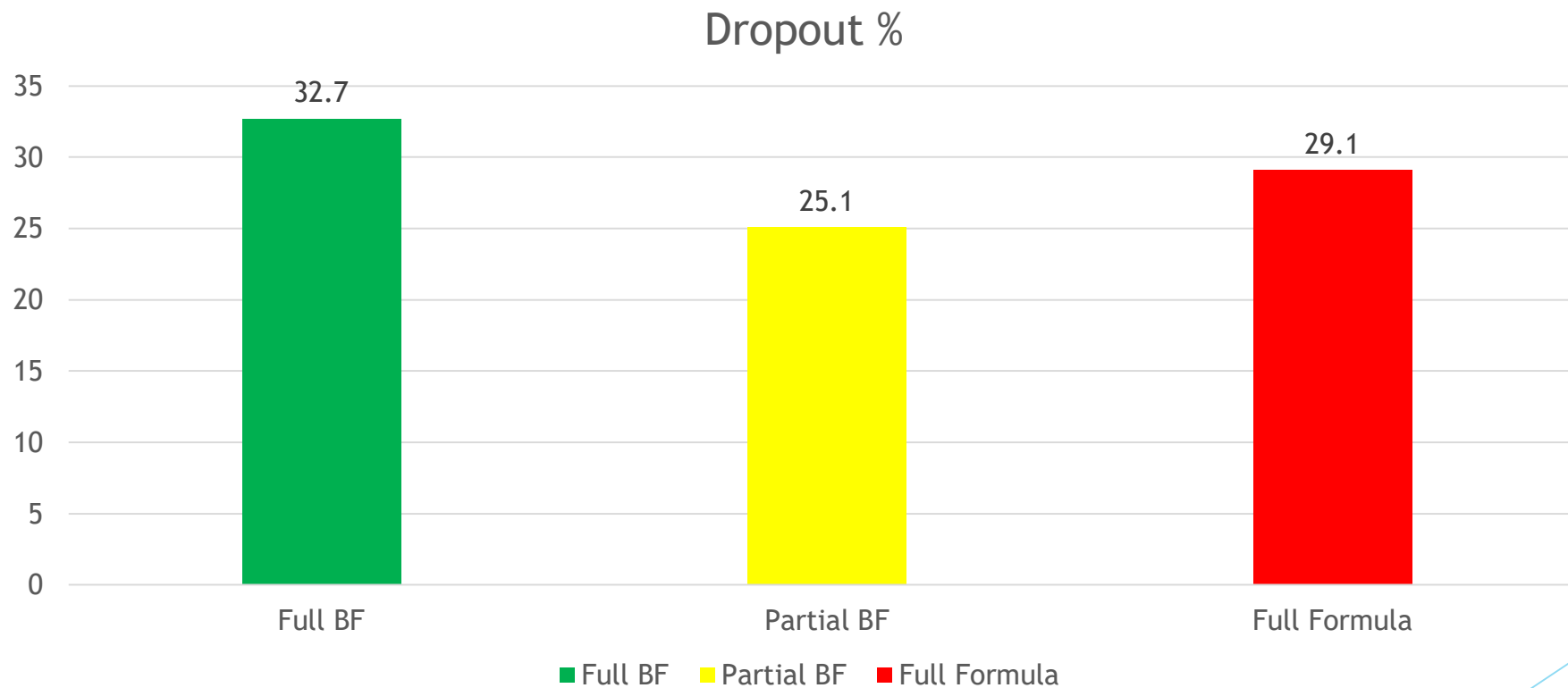
# Distribution of Total Gap Days in A Year



# Application: Dropout before 1<sup>st</sup> B-Day

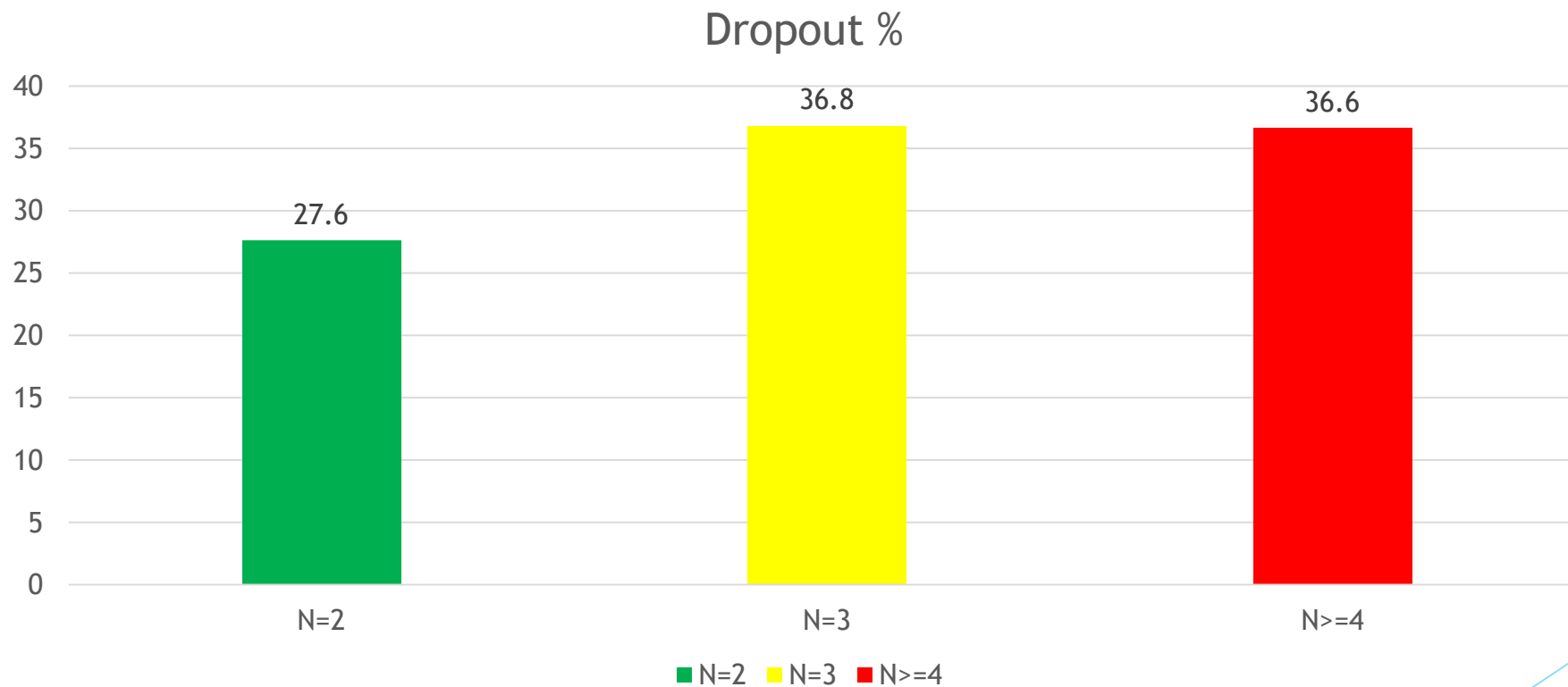
- ▶ Dropout:
  - ▶ No active WIC benefit redemption or participation activities for 3 months since last benefit ending date
- ▶ What's the predictor of dropout before 1<sup>st</sup> Birthday?
  - ▶ Breastfeeding status?
  - ▶ Number of participants in the households?
  - ▶ Race/ethnicity?
  - ▶ Mom's age?
- ▶ Here's the answer based on binary analyses

# Dropout Before 1<sup>st</sup> B-Day by Breastfeeding Status



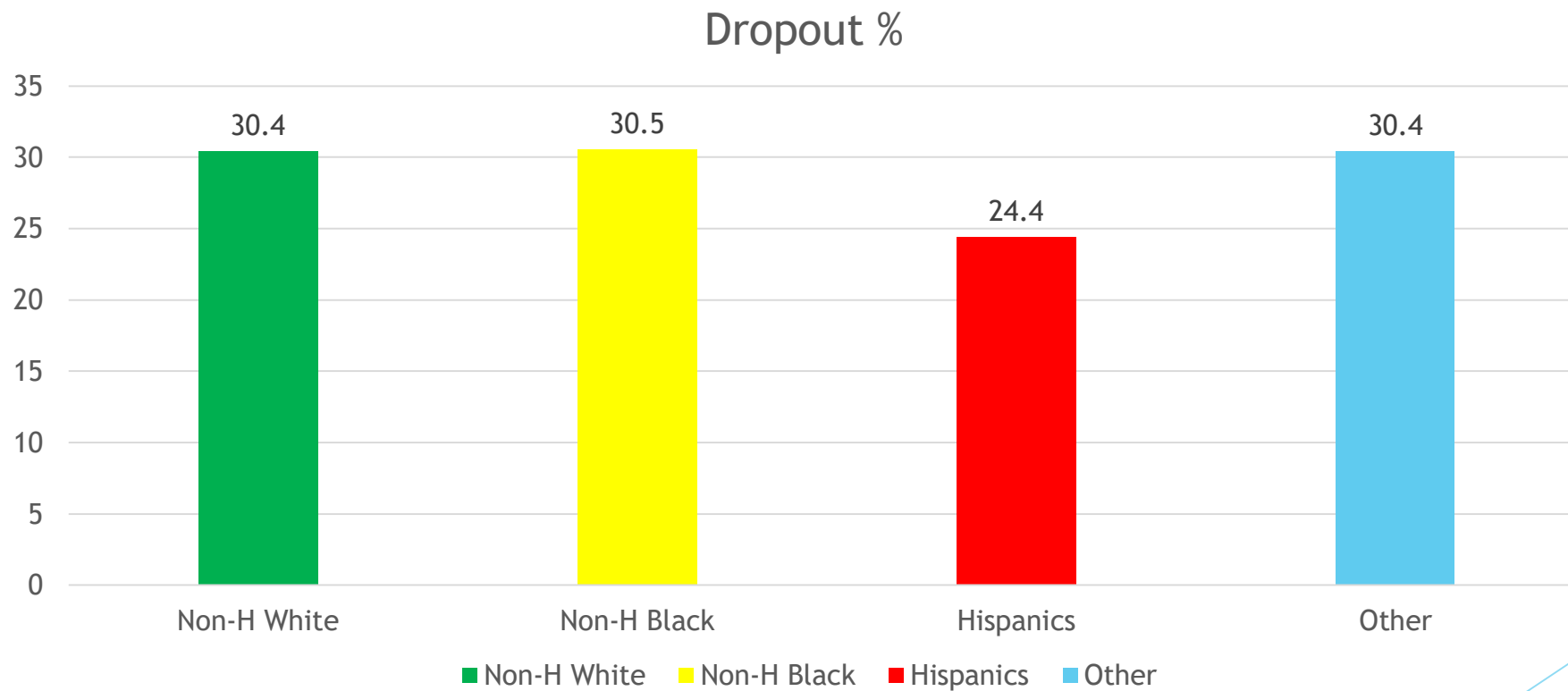
**P<0.001**

# Dropout Before 1<sup>st</sup> B-Day by # of Participants in the Households



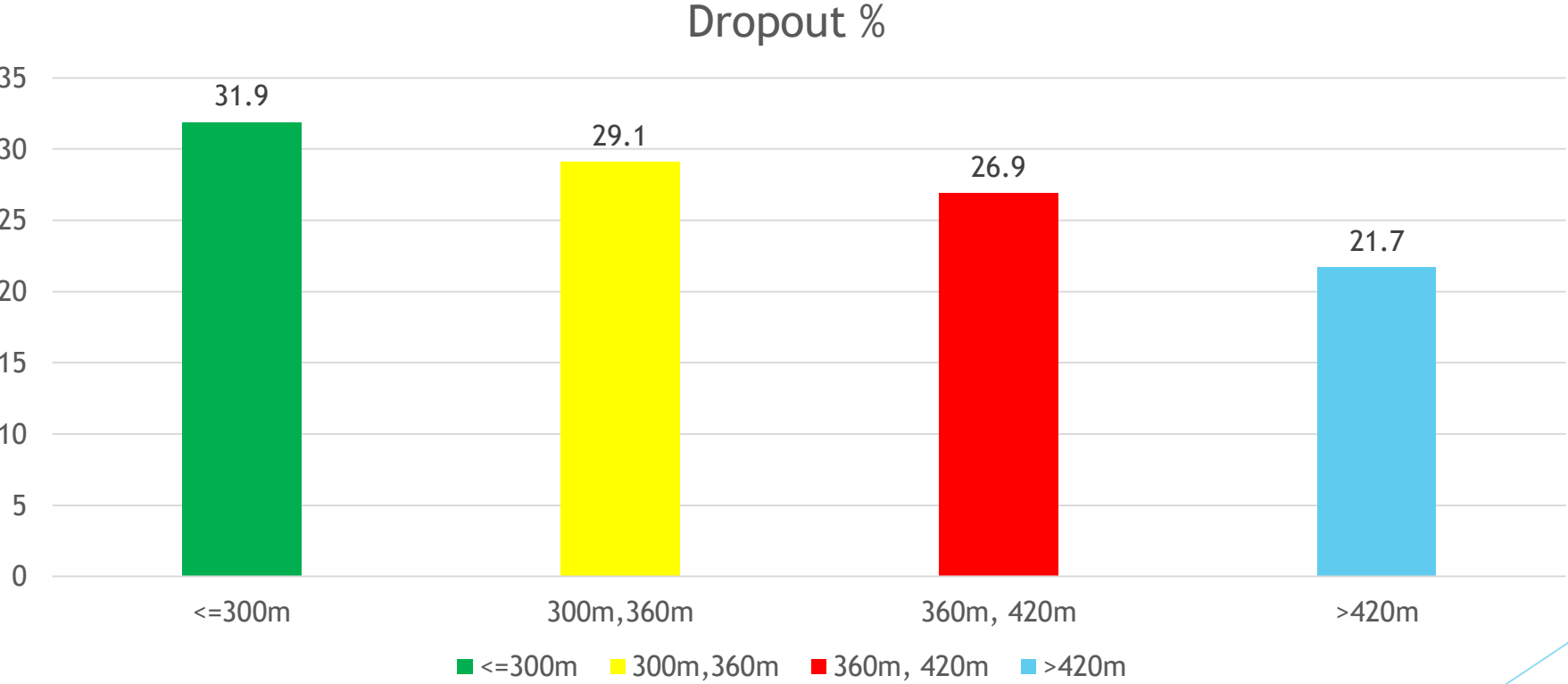
$P < 0.001$

# Dropout Before 1<sup>st</sup> B-Day by Race/Ethnicity



**P<0.001**

# Dropout Before 1<sup>st</sup> 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

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

\*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

- ▶ USDA/FNS EBT Operation Rules (2014)
- ▶ 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

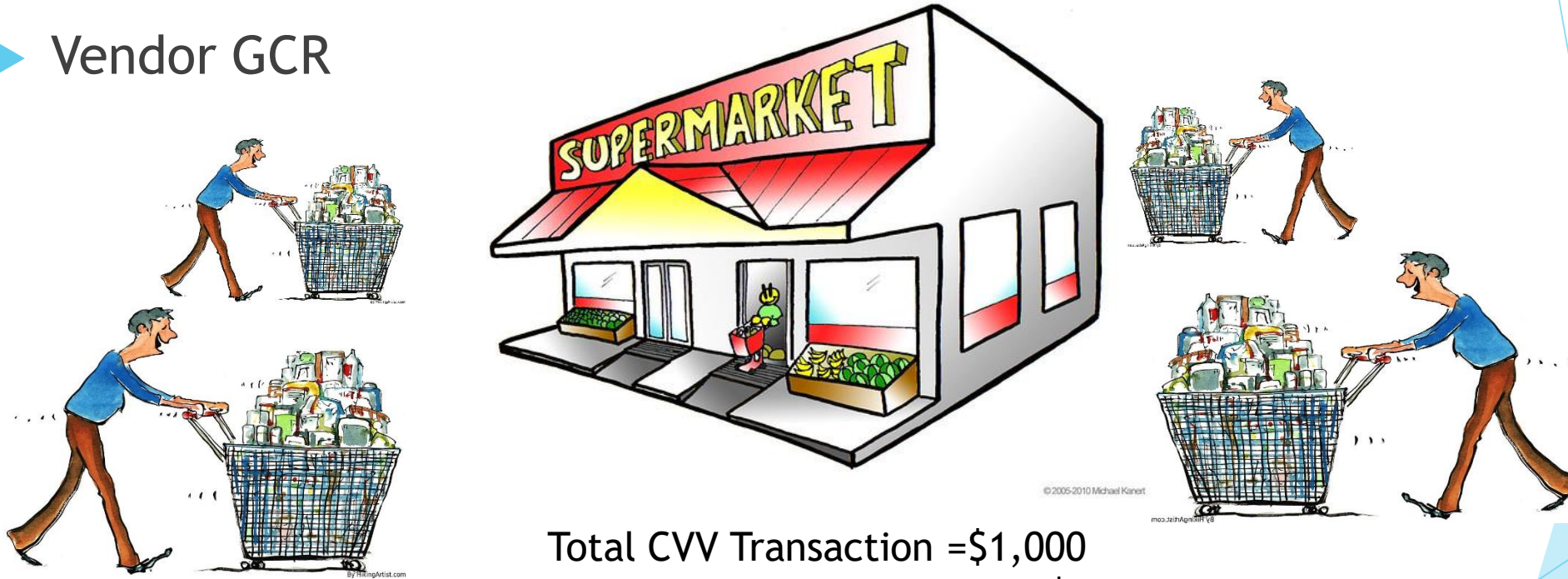
- ▶ After EBT adoption in Virginia in May 2014, optional on full mapping or partial mapping
- ▶ Vendor variations
- ▶ Full mapping stores
  - ▶ No generic code redemption at all
- ▶ Full mapping stores that allow generic codes
  - ▶ Cashiers can enter generic codes occasionally to process
- ▶ Partial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

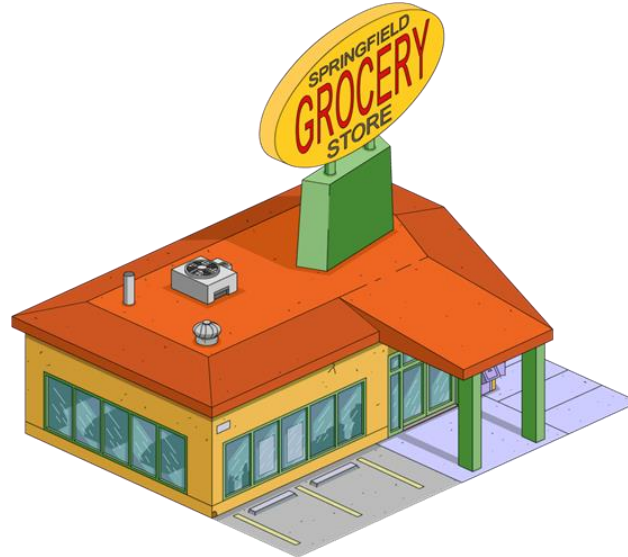
Full Mapping Store



$0 \leq \text{GCR} < 100\%$

© 2005-2010 Michael Kinott

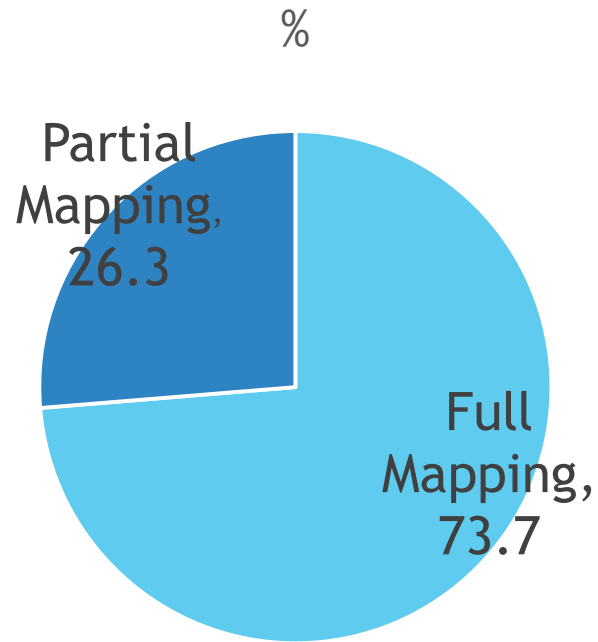
Partial Mapping Store



$\text{GCR} = 100\%$

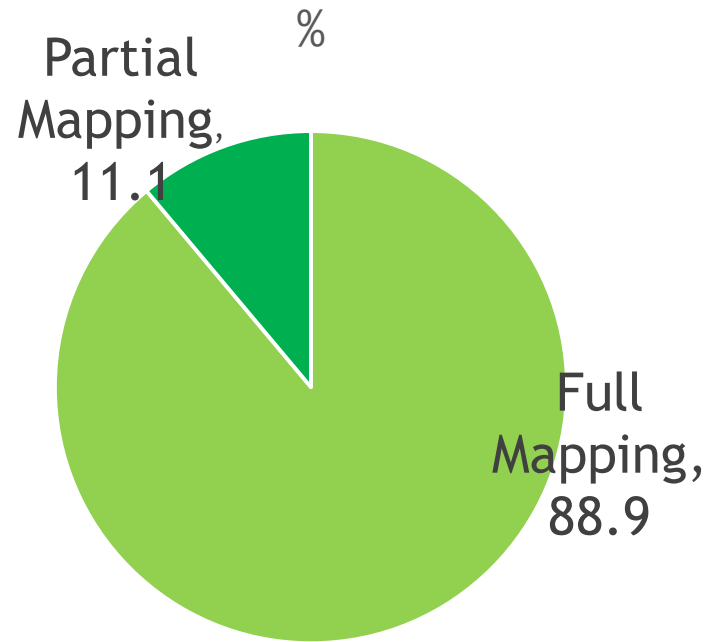


# Distribution of Full vs. Partial Mapping Vendors (N=849)



■ Full Mapping ■ Partial Mapping

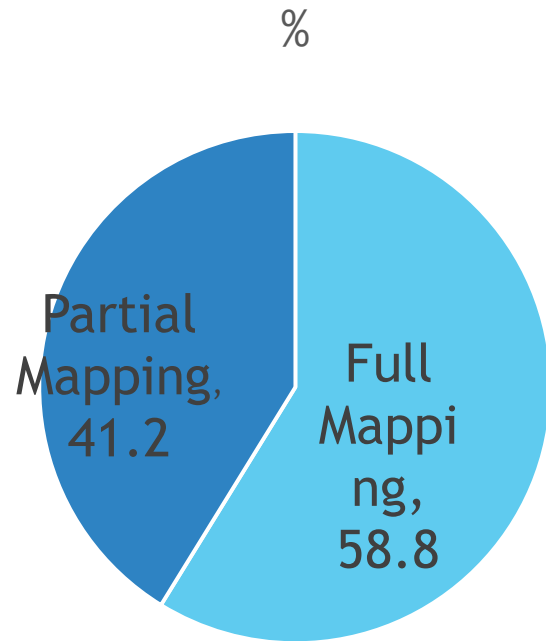
**Urban Vendors**  
**(N=623)**  
Mean GCR=31.9%



■ Full Mapping ■ Partial Mapping

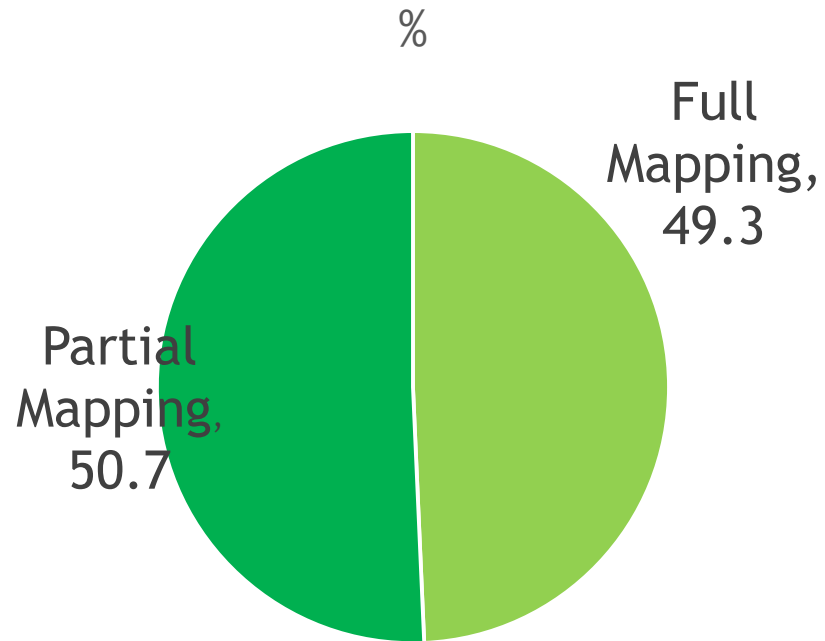
**Rural Vendors**  
**(N=226)**  
Mean GCR=13.4%

# Distribution of Full vs. Partial Mapping Vendors (N=849)



■ Full Mapping ■ Partial Mapping

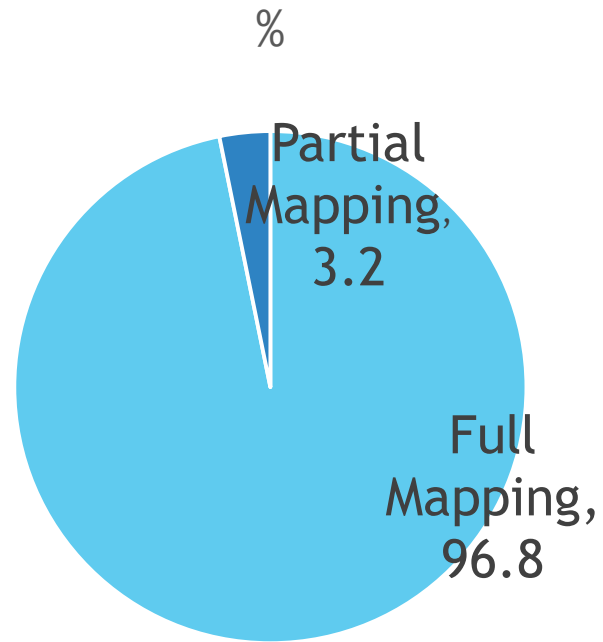
**Large Vendors**  
**(N=308)**  
Mean GCR=47.7%



■ Full Mapping ■ Partial Mapping

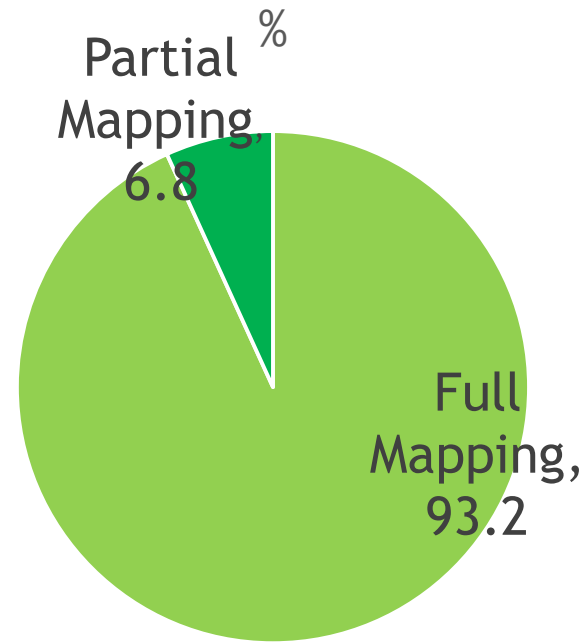
**Small Vendors**  
**(N=73)**  
Mean GCR=49.6%

# Distribution of Full vs. Partial Mapping Vendors (N=849)



■ Full Mapping ■ Partial Mapping

**Medium Plus Vendors (N=188)**  
Mean GCR=8.2%



■ Full Mapping ■ Partial Mapping

**Medium Vendors (N=280)**  
Mean GCR=10.8%

# Generic Code Rate (GCR)

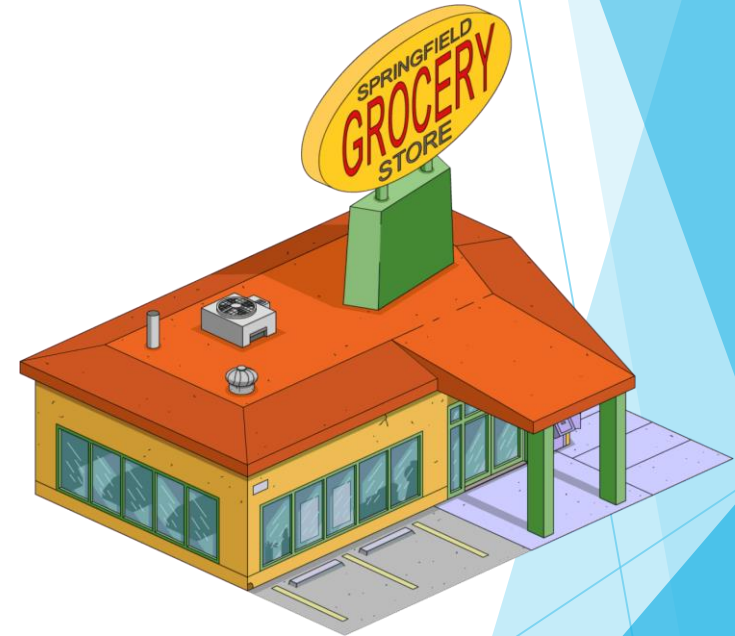
## ▶ Household GCR



Full Mapping Store  
CVV redeemed \$10



GCR =  $\$9 / (\$10 + \$9)$   
= 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) =
  - ▶ # of partial mapping vendors visited / 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

	Coefficient	P-Value
Race/Ethnicity		
N-H White	Reference Group	
N-H Black	-0.026	<0.01
Hispanic	0.048	<0.01
Others	0.063	<0.01



# Results: Participant Factors

	Coefficient	P-Value
Race/Ethnicity		
N-H White	Reference Group	
N-H Black	-0.026	<0.01
Hispanic	0.048	<0.01
Others	0.063	<0.01
# of Participants		
1	Reference Group	
2	-0.026	<0.01
≥3	-0.019	<0.01

# Results: Vendor Factors

	Coefficient	P-Value
Most Visited Vendor Type		
Rural	Reference Group	
Urban	0.014	<0.01

# Results: Vendor Factors

	Coefficient	P-Value
Most Visited Vendor Type		
Rural	Reference Group	
Urban	0.014	<0.01
Most Visited Vendor Type	0.048	<0.01
Large	Reference Group	
Medium plus	-0.001	>0.05
Medium	-0.004	<0.01
Small	-0.022	<0.01

# Results: Vendor Factors

	Coefficient	P-Value
Most Visited Vendor Type		
Rural	Reference Group	
Urban	0.014	<0.01
Most Visited Vendor Type	0.048	<0.01
Large	Reference Group	
Medium plus	-0.001	>0.05
Medium	-0.004	<0.01
Small	-0.022	<0.01
<b>Partial Mapping Vendor Rate</b>	<b>-0.002</b>	<b>&lt;0.01</b>

More exposure to Partial Mapping Vendors, lower CVV Redemption Rate

# Adventure to Hidden World Continues

## Households in Urban Area

	Model 1 Most Visited Vendor is Large	Model 2 Most Visited Vendor is Medium Plus	Model 3 Most Visited Vendor is Medium	Model 4 Most Visited Vendor is Small
PMVR	-0.104	0.147	0.197	0.161
P-Value	<0.01	<0.01	<0.01	<0.01

More exposure to partial mapping stores **increases** the redemption rate, except in large vendor group

# Adventure to Hidden World Continues

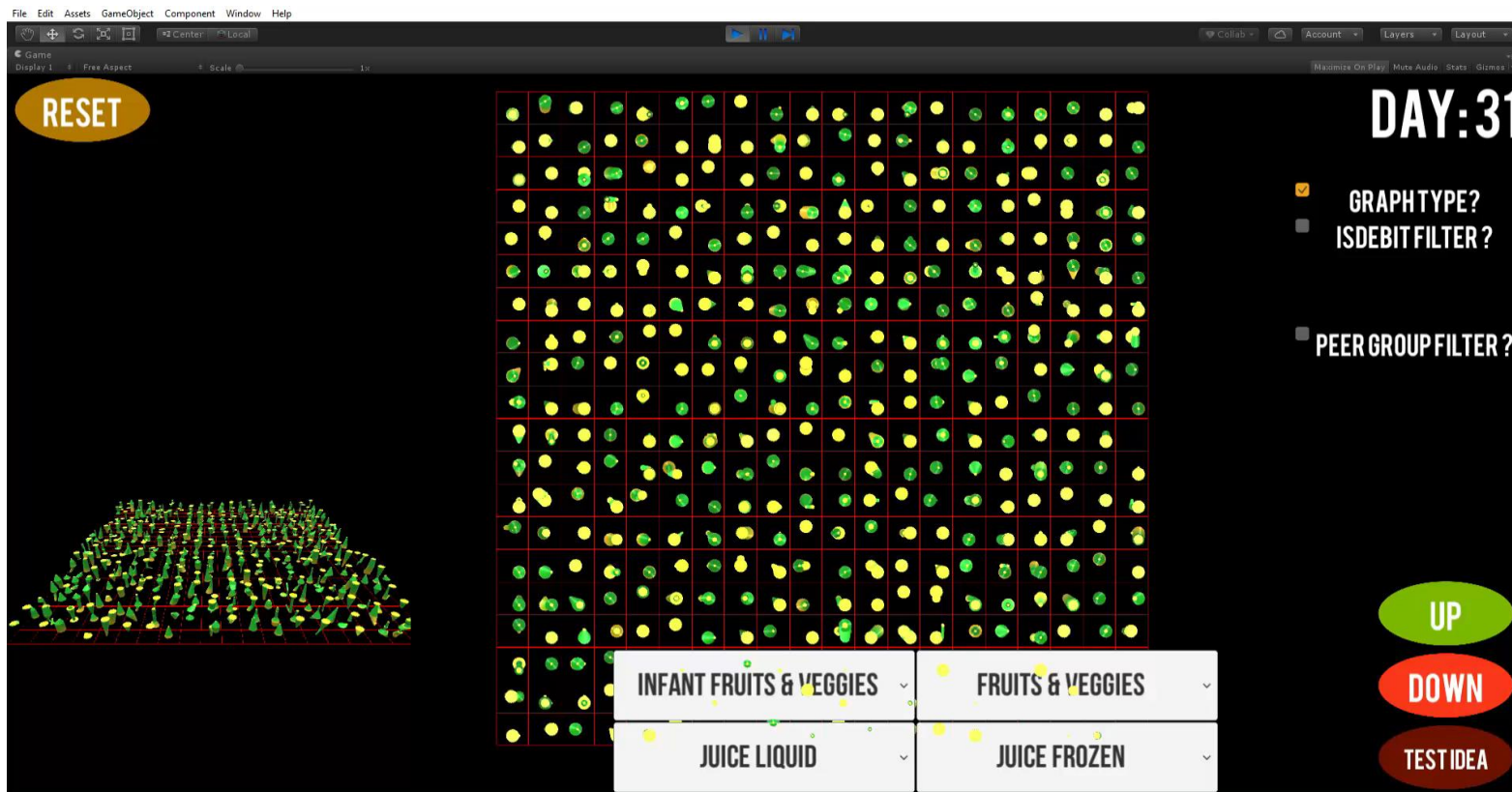
## Households in Rural Area

	Model 1 Most Visited Vendor is Large	Model 2 Most Visited Vendor is Medium Plus	Model 3 Most Visited Vendor is Medium	Model 4 Most Visited Vendor is Small
PMVR	-0.236	-0.209	1.039	-0.361
P-Value	>0.05	<0.01	<0.01	<0.01

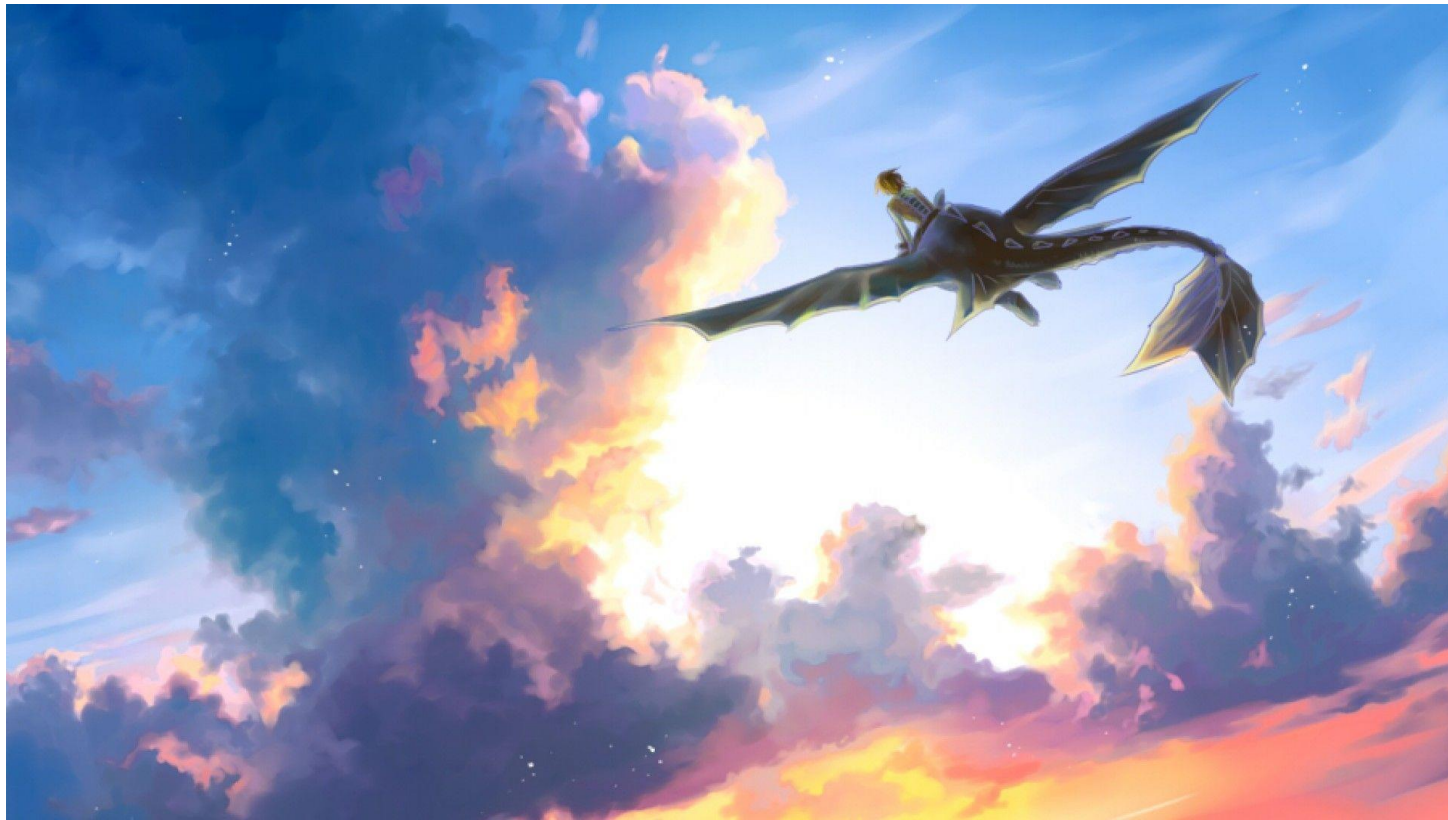
More exposure to partial mapping stores **decreases** the redemption rate except in medium store

**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](https://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)



*Feel free to contact me at anytime!*  
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