How Individuals Smooth Spending: Evidence from the 2013 Government Shutdown Using Account Data

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Financial Literacy Seminar

George Washington University and Federal Reserve Board
December 2015
Acknowledgements

Collaborators

Mike Gelman (Michigan), Shachar Kariv (Berkeley), Dan Silverman (ASU), Steven Tadelis (Berkeley)

Financial Support

Sloan Foundation

NSF-Census Research Network (SES 1131500)
Papers

“Harnessing Naturally Occurring Data to Measure the Response of Spending to Income.” *Science* (July 2014)

Work in progress

• Tax refunds
• Gas prices and spending
• Liquidity over pay-cycle
• Time series of spending and income
Ambitions for time series

- Real-time, weekly series of spending and income
- Augment official time series, especially to address extrapolation/turning point problems
- Challenges
  - Short time series (start Dec 2012)
  - Evolution of sample
  - Seasonal/holiday/trading day/payday effects
Leading Methods: Surveys and Administrative Records

Surveys of individuals are comprehensive but ...

- Self-reported
- Typically low frequency
  - Long, varying, and staggered reporting intervals
  - Infrequent reports
  - Published with considerable lag

Administrative records are accurate, high frequency, and timely but ...

- Not comprehensive
- Large fractions of expenditure, portfolio, or income are missing
Dataset from Mobile Financial App

Timely and high-frequency
• Daily feed

Accurate
• Administrative records of actual transactions and account balances

Comprehensive
• Across individuals: covering a broad spectrum of U.S. population
• Within individual: all transactions and balances from an individual’s checking, saving, credit card, investment accounts

Naturally occurring
• Made available at no additional cost, and de-identified
Some Challenges of Data

• No direct information on demographics
• Data are raw, not organized for research
• Spending is not pre-categorized
• Sample is not randomly selected
Financial App

• App for mobile phones, tablets, and the web
• Has registered more than 10 million registered users 2007
  – Pilot sample of 75,000
  – Now following 1,000,000+ users
• Users can integrate information from nearly any financial account with a web-based portal
• Users provide app with the credentials necessary to access these portals and, every day, app automatically logs into and scrapes the associated webpages
Who is in App?

Comparison of demographics

• App: Third-party data based on email
• ACS
<table>
<thead>
<tr>
<th>Age</th>
<th>App</th>
<th>ACS</th>
</tr>
</thead>
<tbody>
<tr>
<td>18–20</td>
<td>0.6</td>
<td>5.7</td>
</tr>
<tr>
<td>21–24</td>
<td>5.3</td>
<td>7.4</td>
</tr>
<tr>
<td>25–34</td>
<td>37.9</td>
<td>17.5</td>
</tr>
<tr>
<td>35–44</td>
<td>30.1</td>
<td>17.0</td>
</tr>
<tr>
<td>45–54</td>
<td>15.0</td>
<td>18.4</td>
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<tr>
<td>55–64</td>
<td>7.8</td>
<td>16.1</td>
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<tr>
<td>65+</td>
<td>3.5</td>
<td>18.0</td>
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<tr>
<td>Gender</td>
<td>App</td>
<td>ACS</td>
</tr>
<tr>
<td>--------</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>Male</td>
<td>59.9</td>
<td>48.6</td>
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<tr>
<td>Female</td>
<td>40.1</td>
<td>51.4</td>
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## Education

<table>
<thead>
<tr>
<th></th>
<th>App</th>
<th>ACS</th>
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<tbody>
<tr>
<td>Less than college</td>
<td>70.0</td>
<td>62.9</td>
</tr>
<tr>
<td>College</td>
<td>24.1</td>
<td>26.2</td>
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<tr>
<td>Graduate school</td>
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<td>Region</td>
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<td>------</td>
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<tr>
<td>Northeast</td>
<td>20.6</td>
<td>17.8</td>
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<tr>
<td>Midwest</td>
<td>14.6</td>
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<tr>
<td>South</td>
<td>36.7</td>
<td>37.4</td>
</tr>
<tr>
<td>West</td>
<td>28.1</td>
<td>23.4</td>
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Transactions and accounts

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>$P_5$</th>
<th>$P_{25}$</th>
<th>$P_{50}$</th>
<th>$P_{75}$</th>
<th>$P_{95}$</th>
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<tbody>
<tr>
<td>Daily transactions</td>
<td>4.54</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>13</td>
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<tr>
<td>Credit card</td>
<td>1.23</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Checking account</td>
<td>3.03</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>Saving account</td>
<td>0.22</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Accounts</td>
<td>5.84</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>Credit card</td>
<td>3.58</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>Checking account</td>
<td>1.35</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Saving account</td>
<td>0.79</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Notes: In total, the 57,731,354 transactions are generated from 72,902 unique users over the study period.
## Account balance

<table>
<thead>
<tr>
<th>Panel (a): Bank</th>
<th>Mean</th>
<th>$P_5$</th>
<th>$P_{25}$</th>
<th>$P_{50}$</th>
<th>$P_{75}$</th>
<th>$P_{95}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>$14,415$</td>
<td>$100$</td>
<td>$700$</td>
<td>$2,200$</td>
<td>$7,900$</td>
<td>$55,400$</td>
</tr>
<tr>
<td>Checking</td>
<td>$6,969$</td>
<td>$100$</td>
<td>$500$</td>
<td>$1,400$</td>
<td>$3,800$</td>
<td>$23,100$</td>
</tr>
<tr>
<td>Saving</td>
<td>$6,476$</td>
<td>$0$</td>
<td>$0$</td>
<td>$400$</td>
<td>$2,500$</td>
<td>$25,200$</td>
</tr>
<tr>
<td>Money Market</td>
<td>$12,076$</td>
<td>$0$</td>
<td>$100$</td>
<td>$900$</td>
<td>$7,700$</td>
<td>$57,400$</td>
</tr>
<tr>
<td>C.D.</td>
<td>$12,734$</td>
<td>$0$</td>
<td>$0$</td>
<td>$500$</td>
<td>$4,000$</td>
<td>$39,200$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b): Credit Card</th>
<th>Mean</th>
<th>$P_5$</th>
<th>$P_{25}$</th>
<th>$P_{50}$</th>
<th>$P_{75}$</th>
<th>$P_{95}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balance</td>
<td>$7,228$</td>
<td>$200$</td>
<td>$1,400$</td>
<td>$3,600$</td>
<td>$8,500$</td>
<td>$26,100$</td>
</tr>
<tr>
<td>Credit Limit</td>
<td>$23,019$</td>
<td>$800$</td>
<td>$4,200$</td>
<td>$11,900$</td>
<td>$29,500$</td>
<td>$81,800$</td>
</tr>
<tr>
<td>Utilization Ratio</td>
<td>0.48</td>
<td>0.02</td>
<td>0.15</td>
<td>0.45</td>
<td>0.78</td>
<td>1.00</td>
</tr>
<tr>
<td>Revolving Debt</td>
<td>$5,828$</td>
<td>$1,200$</td>
<td>$2,100$</td>
<td>$3,500$</td>
<td>$6,700$</td>
<td>$18,000$</td>
</tr>
<tr>
<td>APR</td>
<td>18.46%</td>
<td>10%</td>
<td>15%</td>
<td>18%</td>
<td>23%</td>
<td>27%</td>
</tr>
</tbody>
</table>
Measuring income and expenditures from transactions

**Total Income**

**Paycheck and Social Security**
Weekly Spending: Total

(a) Total (Full sample)

(b) Total (Linked users)
Weekly Spending: Non-Recurring

(c) Non-Recurring (Full sample)

(d) Non-Recurring (Linked users)
Weekly Spending: Coffee Shop and Fast Food

(e) Fast Food and Coffee Shop (Full sample)

(f) Fast Food and Coffee Shop (Linked users)
Average Propensity to Spend (Monthly Spending / Monthly Income)

Income quintiles

Spending quintiles
Excess sensitivity to paycheck and Social Security

Data allows

• Identification of payments

• Estimate of response by

  – Type novel classification of spending
  – By liquidity, etc
Response of spending to paycheck

Total

Non-recurring

Coffee shop and fast food
Response of spending to paycheck
Non-recurring spending by liquidity

Low liquidity
Medium liquidity
High liquidity
2013 US government shutdown

Workers subject to shutdown
  — lost 40% of pay in one pay period
  — reimbursed in next pay period

Distinctive experiment:
• *Timing* of income only
  — No wealth effects
• Drop in income
# Government Shutdown of Oct 2013

<table>
<thead>
<tr>
<th></th>
<th>Sunday</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
<th>Saturday</th>
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</thead>
<tbody>
<tr>
<td>Pay period</td>
<td>Sept 22</td>
<td>23</td>
<td>24</td>
<td>25</td>
<td>26</td>
<td>27</td>
<td>28</td>
</tr>
<tr>
<td>Pay period</td>
<td>29</td>
<td>30</td>
<td>Oct 1 Shutdown Begins</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Pay period</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10 First pay date affected by shutdown</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>14</td>
<td>15</td>
<td>16</td>
<td>17 Shutdown Ends</td>
<td>18</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>21</td>
<td>22</td>
<td>23</td>
<td>24 Typical pay date after shutdown</td>
<td>25</td>
<td>26</td>
</tr>
</tbody>
</table>
Aug 21 – 80 House Republicans sign letter urging defunding of Obamacare

Sep 20 – House Republicans approve legislation to defund healthcare while keeping government open

Sep 30 – Senate rejects House bill with measures to defund healthcare

Oct 5 – Bill compensating furloughed employees passed

Oct 1 – Shutdown begins

Oct 17 – Obama signs bill ending shutdown
Treatment and control

*Treatment*

- Federal worker (paycheck memo), and
- Decline in paycheck consistent with shutdown

*Control*

- Other worker on same biweekly pay schedule as government
“Seasonal” interactions

• Day of week
  – Spending
  – Clearing of payments

• Beginning of pay period effects

• Seasonal/holiday/macro effects

→ Having controls with same pay schedule valuable
Average weekly spending
Pre-Shutdown Median Liquidity over the Paycheck Cycle
Diff-in-diff effects of shutdown

\[ y_{i,t} = \sum_{k=1}^{T} \delta_k \times Week_{i,k} + \sum_{k=1}^{T} \beta_k \times Week_{i,k} \times Shut_{i} + \Gamma'X_{i,t} + \varepsilon_{i,t} \]

Specification:

LHS = variable of interest (income, category of spending)
Normalized by average individual spending (daily rate)
Diff-in-diff effects of shutdown

Paycheck income

Total spending
Diff-in-diff effects of shutdown

Non-recurring spending

Recurring spending
Diff-in-diff effects of shutdown

Credit card spending

Credit card balance payments
Diff-in-diff effects of shutdown

Coffee shop and fast food
Diff-in-diff effects of shutdown, Liquid Assets

Normalized by Average Liquid Balance

Normalized by Average Daily Spending
Diff-in-diff effects of shutdown, by liquidity

Non-recurring spending

![Graph showing non-recurring spending over time, categorized by liquidity.]
Diff-in-diff effects of shutdown, by liquidity

Recurring spending

-4 -3 -2 -1 0 1 2 3 4
Spending (Normalized)

Low Liquidity
Medium Liquidity
High Liquidity
Diff-in-diff effects of shutdown, by liquidity

Coffee shop and fast food
Diff-in-diff effects of shutdown, by liquidity

Credit card spending

Credit card balance payments
Diff-in-diff effects of shutdown, Credit Card Balance by "Liquidity Risk"

Notes:  
Horizontal axis is days since August 2013  
Rivolvers only  
Data are by individual credit card account levels  
“At risk” accounts have payment due dates in pay period affected by shutdown
Lessons from shutdown

Puzzle for standard models:
• Very sizeable payment response to a two-week delay in pay

Success for standard models:
• Rearrangement of payments, not consumption

New data essential