



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

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Financial Literacy Seminar

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Acknowledgements

Collaborators

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Papers

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

“How Individuals Smooth Spending: Evidence from the 2013 Government Shutdown Using Account Data.” NBER WP (Revised Oct 2015)

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

Age

	App	ACS
18–20	0.6	5.7
21–24	5.3	7.4
25–34	37.9	17.5
35–44	30.1	17.0
45–54	15.0	18.4
55–64	7.8	16.1
65+	3.5	18.0

Gender

	App	ACS
Male	59.9	48.6
Female	40.1	51.4

Education

	App	ACS
Less than college	70.0	62.9
College	24.1	26.2
Graduate school	6.0	10.9

Region

	App	ACS
Northeast	20.6	17.8
Midwest	14.6	21.5
South	36.7	37.4
West	28.1	23.4

Transactions and accounts

	Mean	P_5	P_{25}	P_{50}	P_{75}	P_{95}
Daily transactions	4.54	1	2	3	6	13
Credit card	1.23	0	0	1	2	5
Checking account	3.03	0	0	2	4	11
Saving account	0.22	0	0	0	0	1
Accounts	5.84	2	3	5	8	12
Credit card	3.58	1	2	3	5	9
Checking account	1.35	0	1	1	2	3
Saving account	0.79	0	0	1	1	2

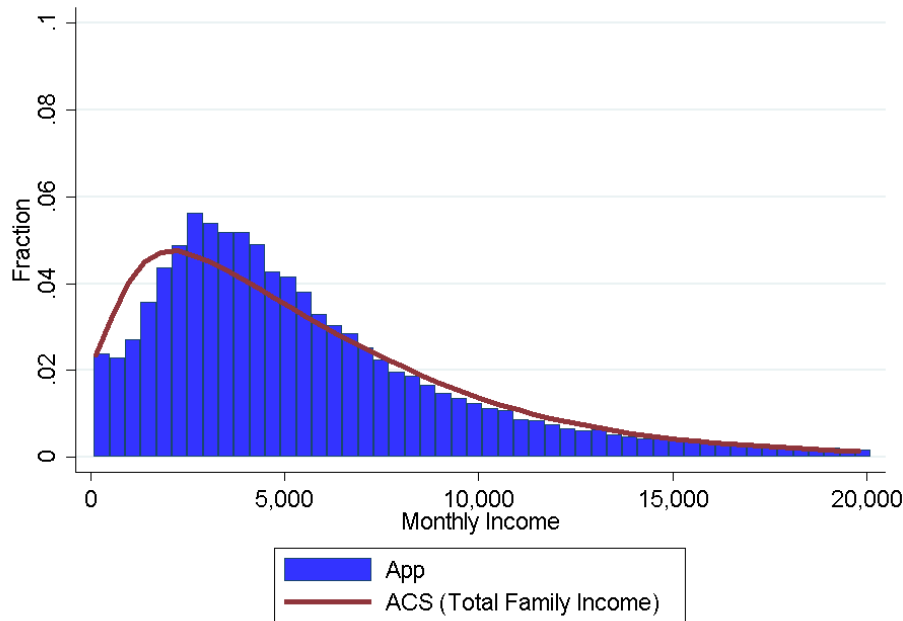
Notes: In total, the 57,731,354 transactions are generated from 72,902 unique users over the study period.

Account balance

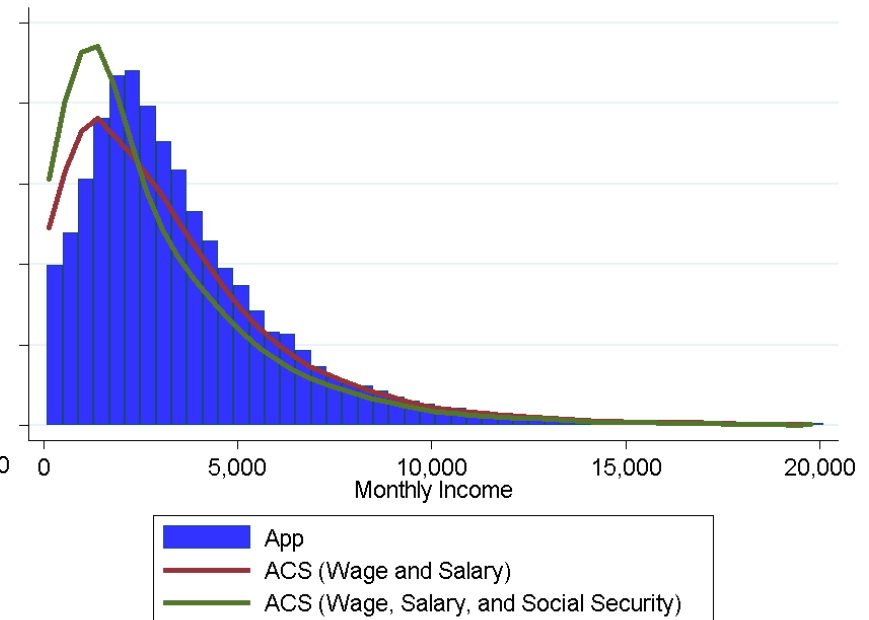
Panel (a): Bank	Mean	P_5	P_{25}	P_{50}	P_{75}	P_{95}
All	\$14,415	\$100	\$700	\$2,200	\$7,900	\$55,400
Checking	\$6,969	\$100	\$500	\$1,400	\$3,800	\$23,100
Saving	\$6,476	\$0	\$0	\$400	\$2,500	\$25,200
Money Market	\$12,076	\$0	\$100	\$900	\$7,700	\$57,400
C.D.	\$12,734	\$0	\$0	\$500	\$4,000	\$39,200
Panel (b): Credit Card	Mean	P_5	P_{25}	P_{50}	P_{75}	P_{95}
Balance	\$7,228	\$200	\$1,400	\$3,600	\$8,500	\$26,100
Credit Limit	\$23,019	\$800	\$4,200	\$11,900	\$29,500	\$81,800
Utilization Ratio	0.48	0.02	0.15	0.45	0.78	1.00
Revolving Debt	\$5,828	\$1,200	\$2,100	\$3,500	\$6,700	\$18,000
APR	18.46%	10%	15%	18%	23%	27%

Measuring income and expenditures from transactions

Total Income

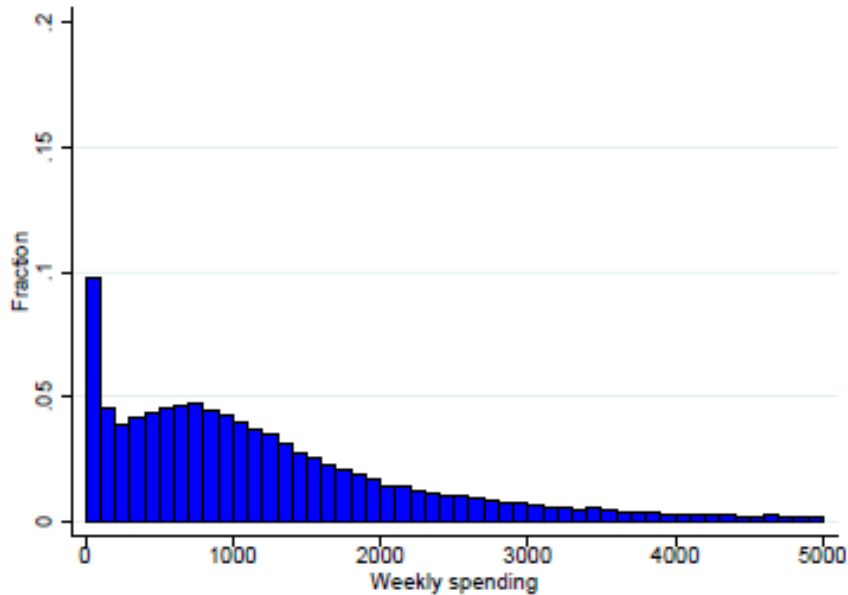


Paycheck and Social Security

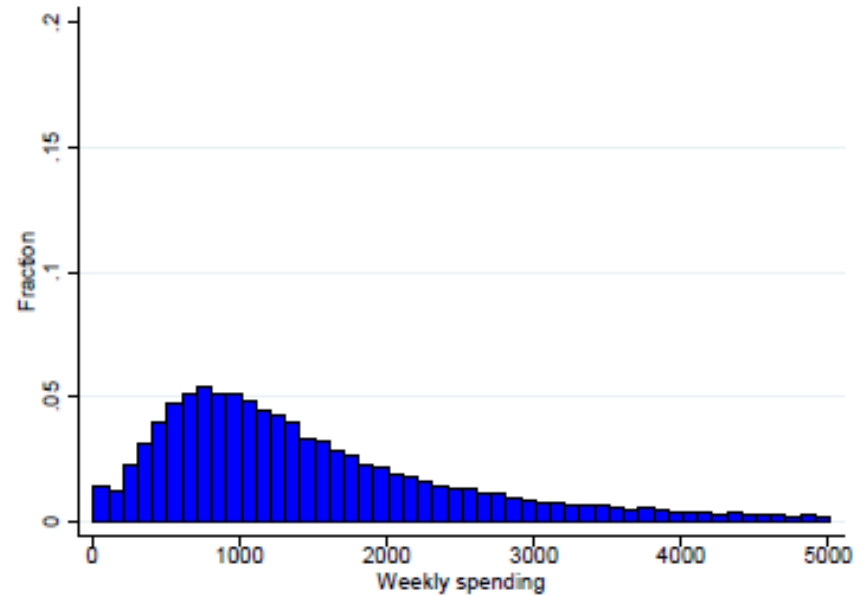


Weekly Spending: Total

(a) Total (Full sample)

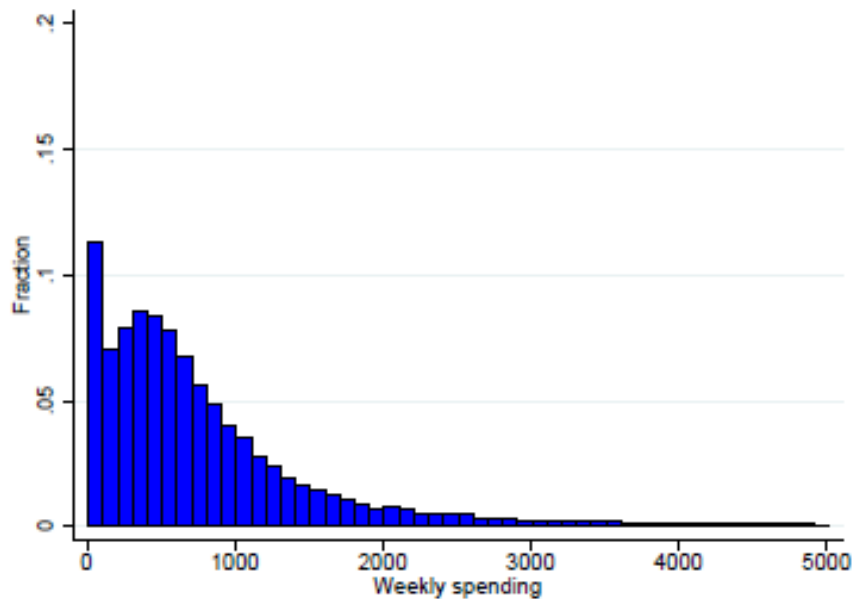


(b) Total (Linked users)

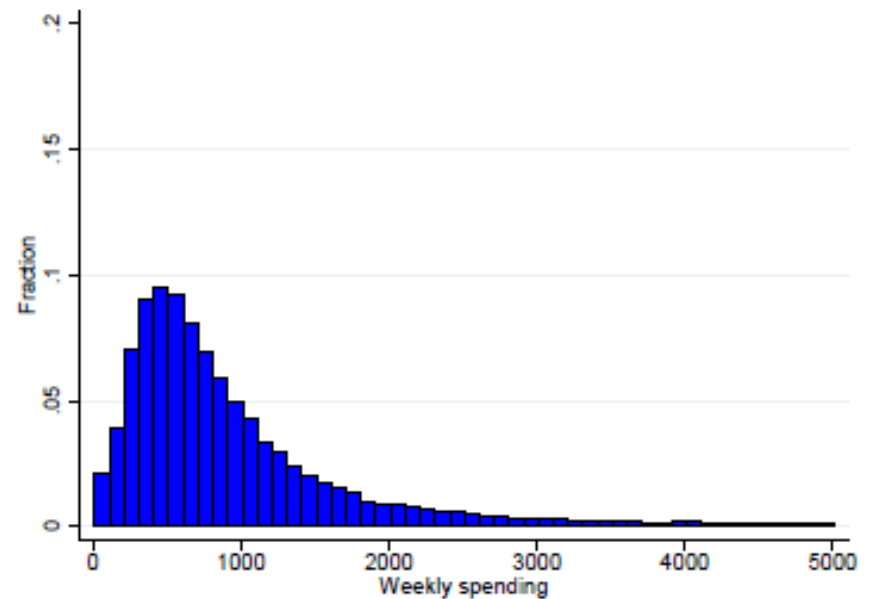


Weekly Spending: Non-Recurring

(c) Non-Recurring (Full sample)

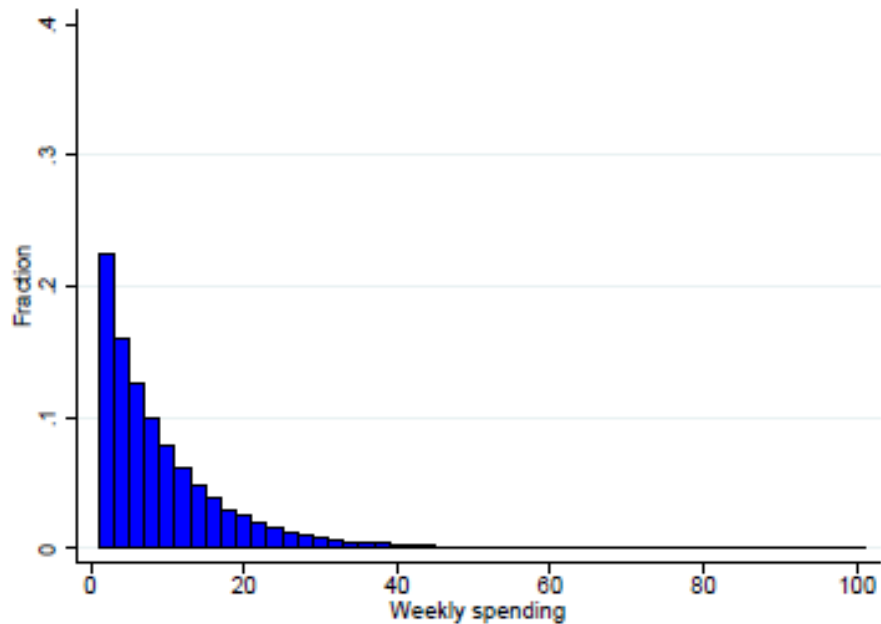


(d) Non-Recurring (Linked users)

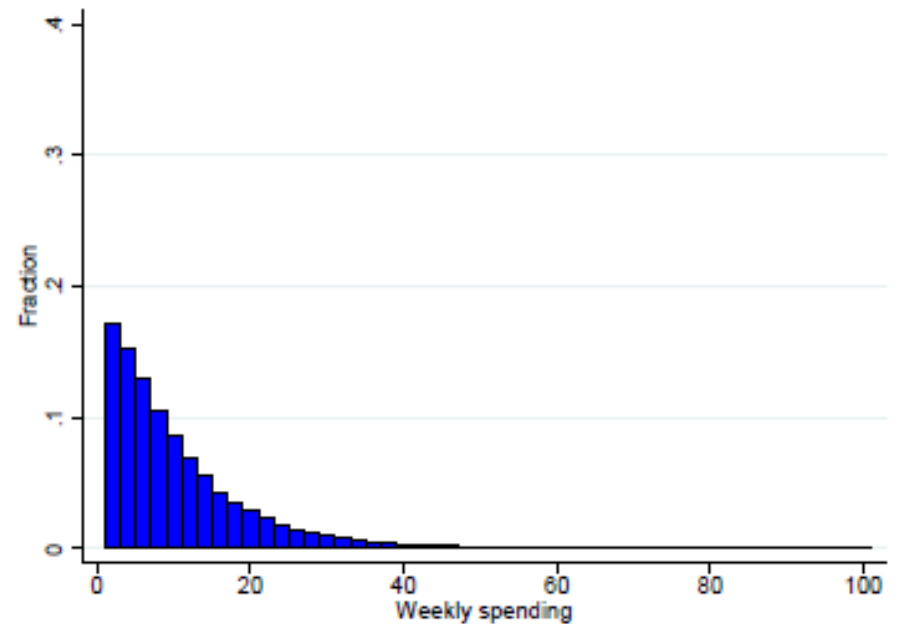


Weekly Spending: Coffee Shop and Fast Food

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

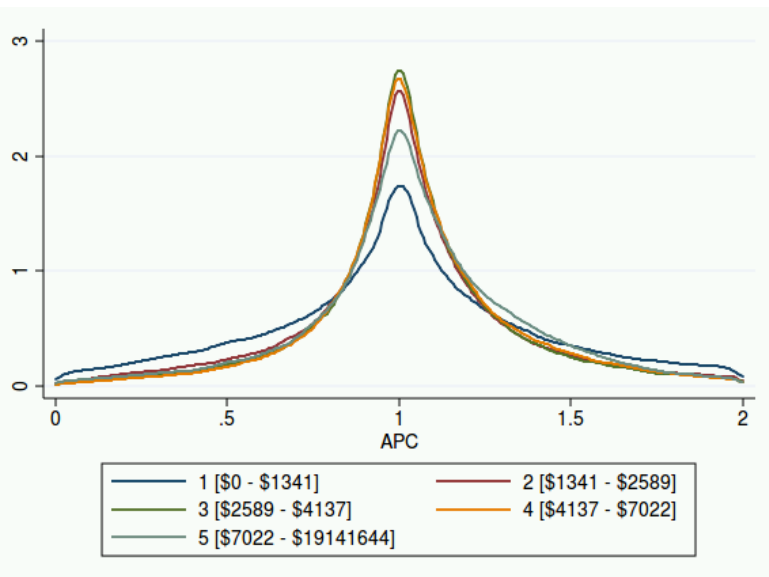


(f) Fast Food and Coffee Shop (Linked users)

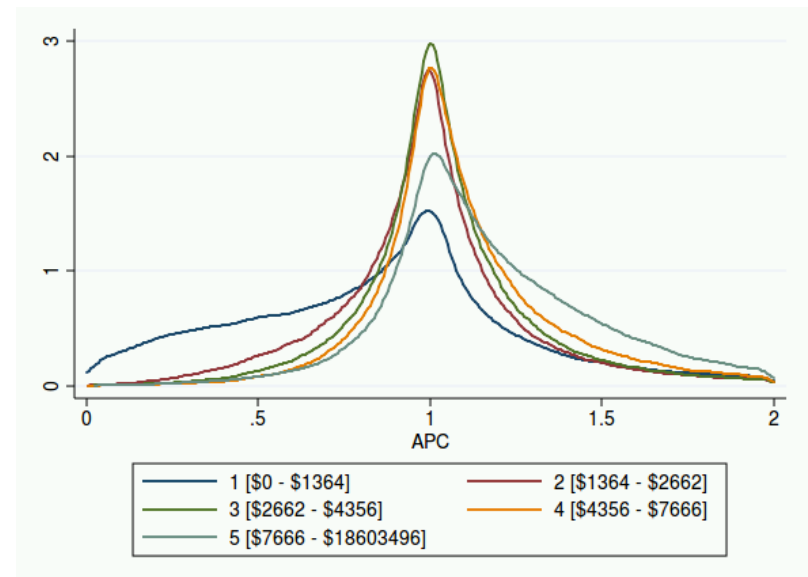


Average Propensity to Spend (Monthly Spending / Monthly Income)

Income quintiles



Spending quintiles

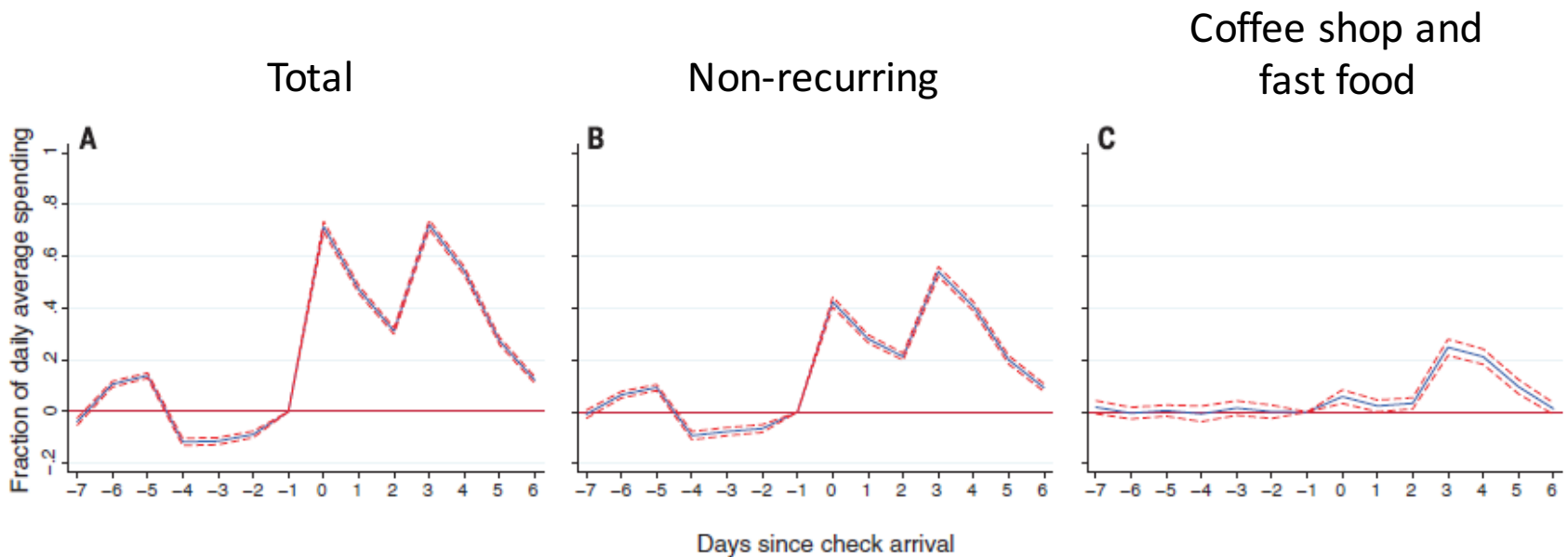


Excess sensitivity to paycheck and Social Security

Data allows

- Identification of payments
- Estimate of response by
 - Type novel classification of spending
 - By liquidity, etc

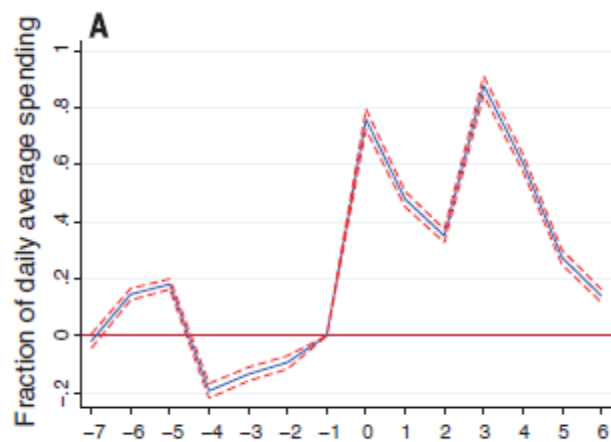
Response of spending to paycheck



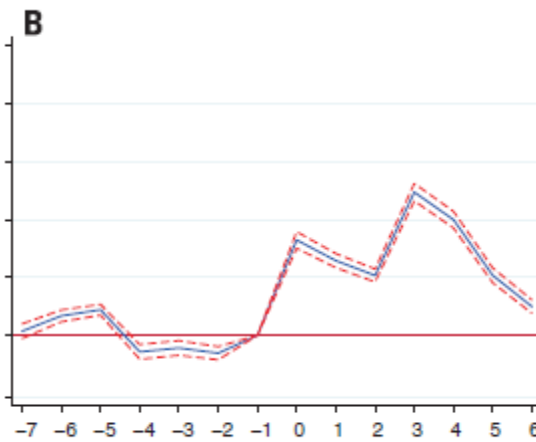
Response of spending to paycheck

Non-recurring spending by liquidity

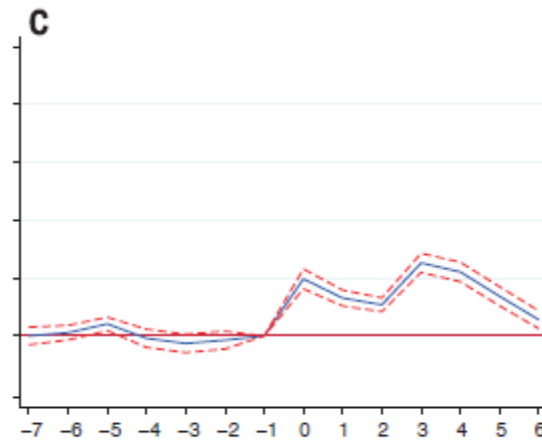
Low liquidity



Medium liquidity



High liquidity



2013 US government shutdown

Workers subject to shutdown

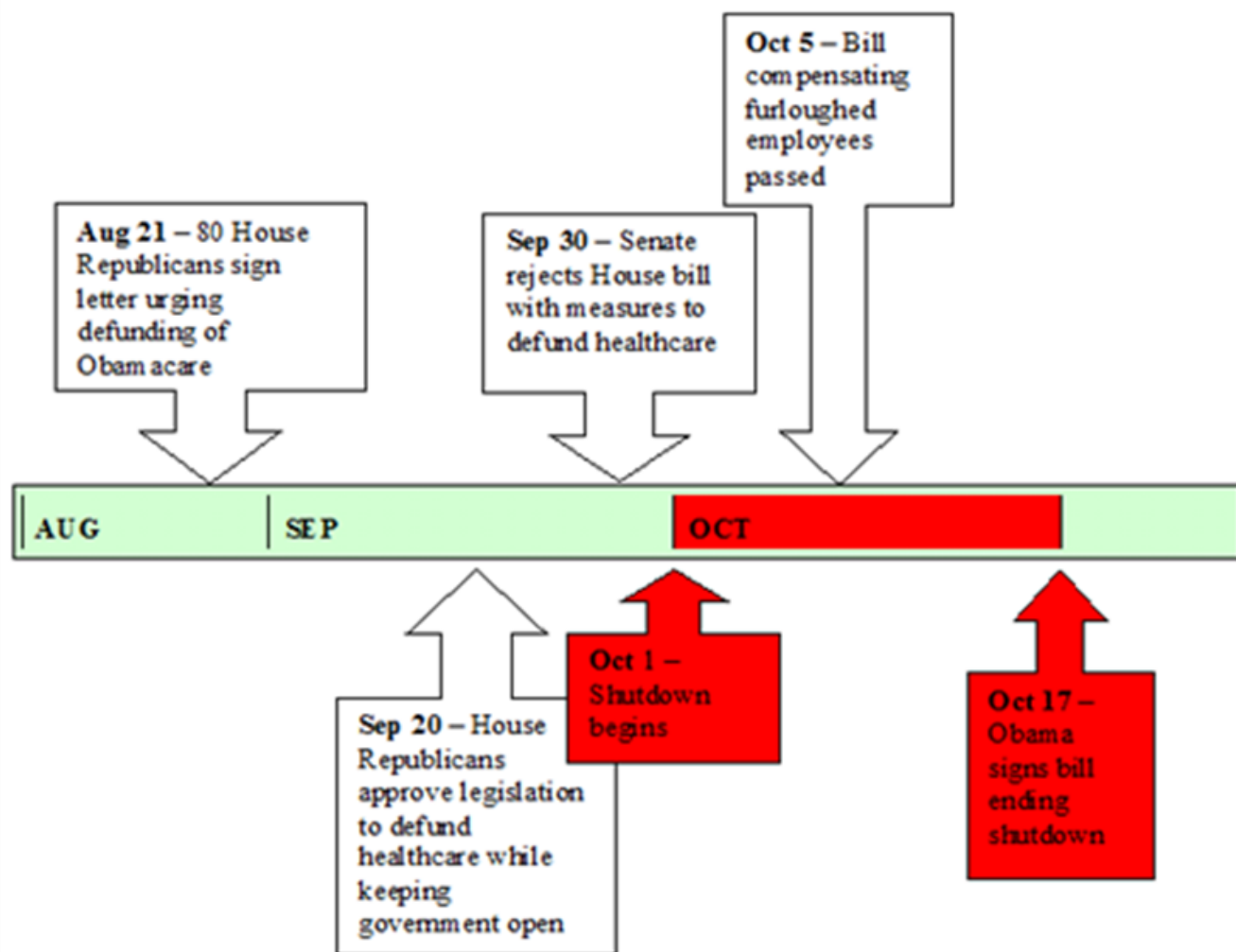
- lost 40% of pay in one pay period
- reimbursed in next pay period

Distinctive experiment:

- *Timing* of income only
 - No wealth effects
- Drop in income

Government Shutdown of Oct 2013

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Pay period	Sept 22	23	24	25	26	27	28
	29	30	Oct 1 Shutdown Begins	2	3	4	5
Pay period	6	7	8	9	10 First pay date affected by shutdown	11	12
	13	14	15	16	17 Shutdown Ends	18	19
	20	21	22	23	24 Typical pay date after shutdown	25	26



Treatment and control

Treatment

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

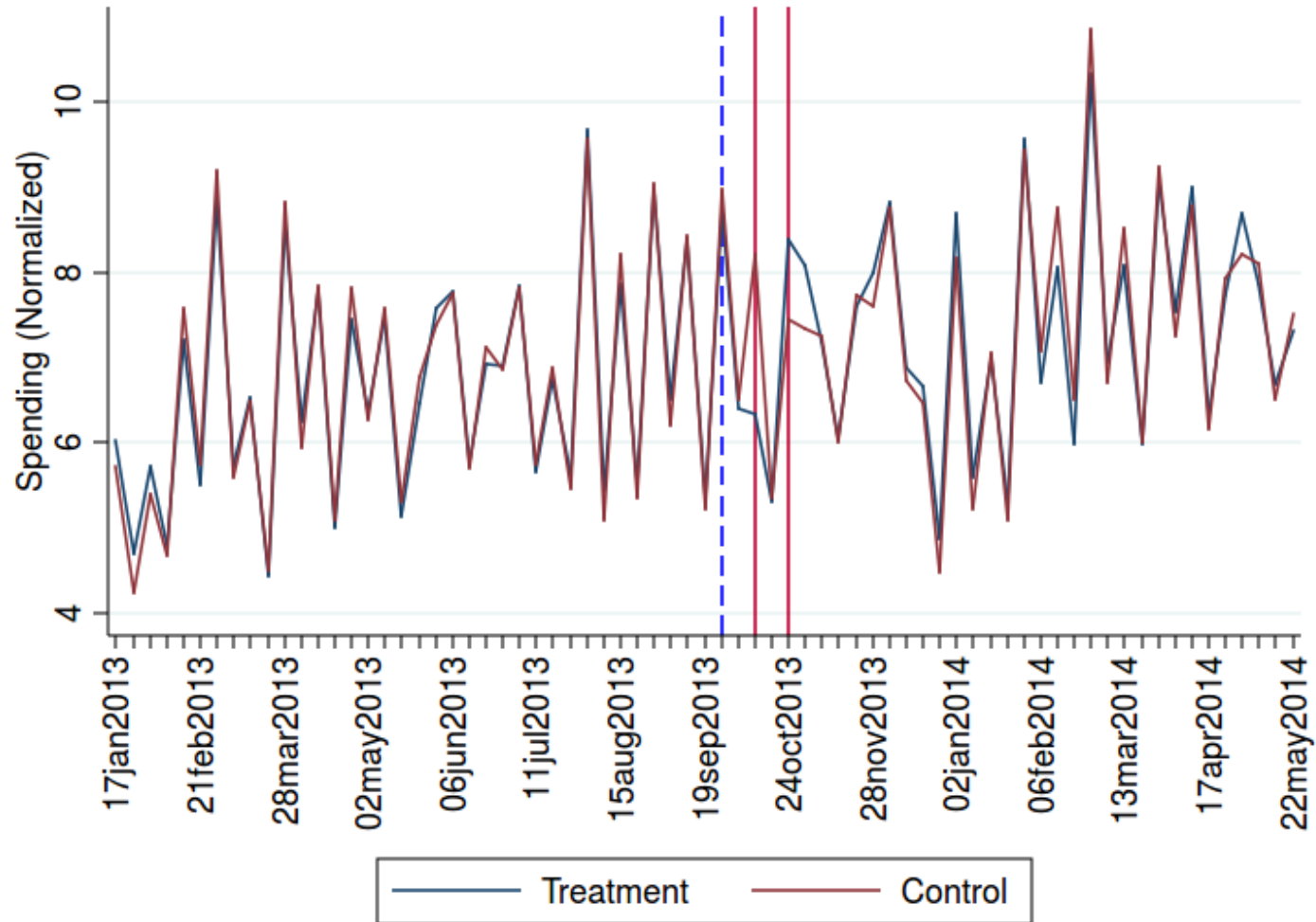
Control

- Other worker on same biweekly pay schedule as government

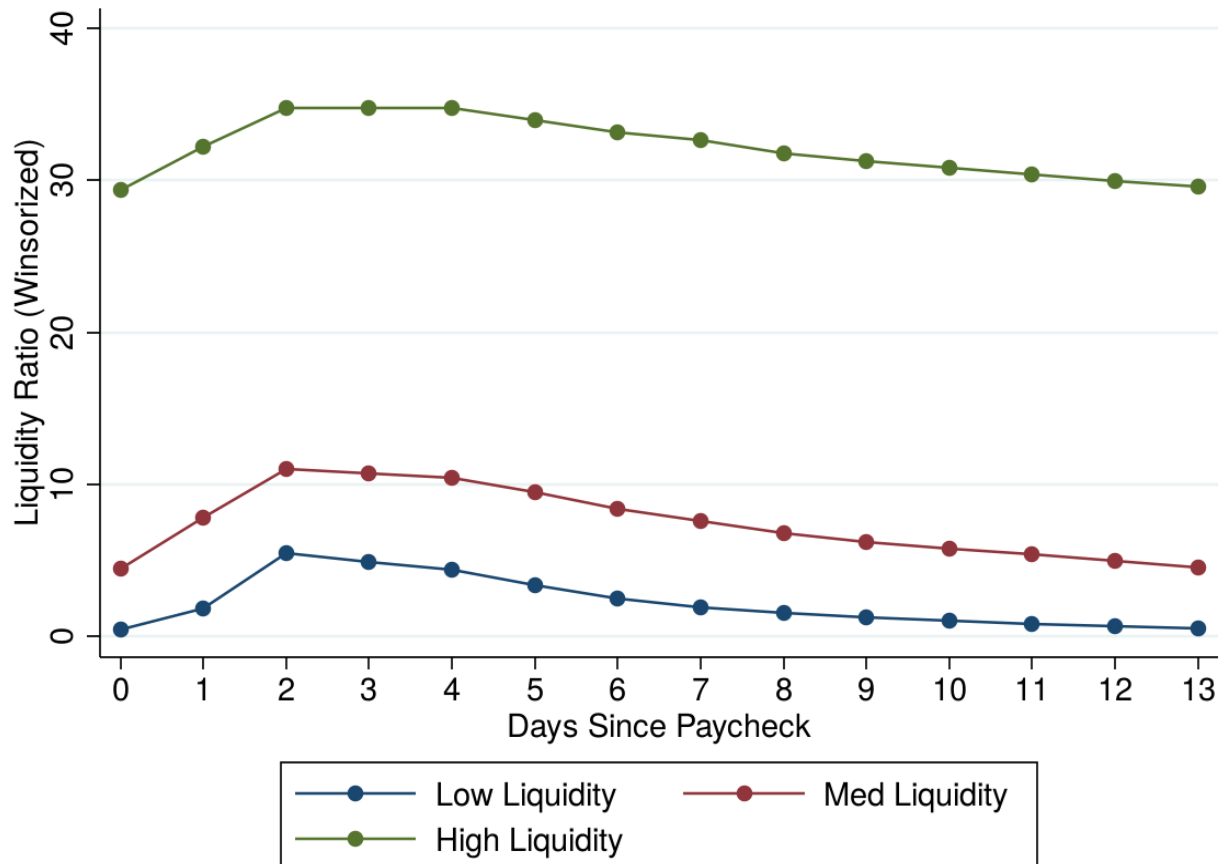
“Seasonal” interactions

- 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

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

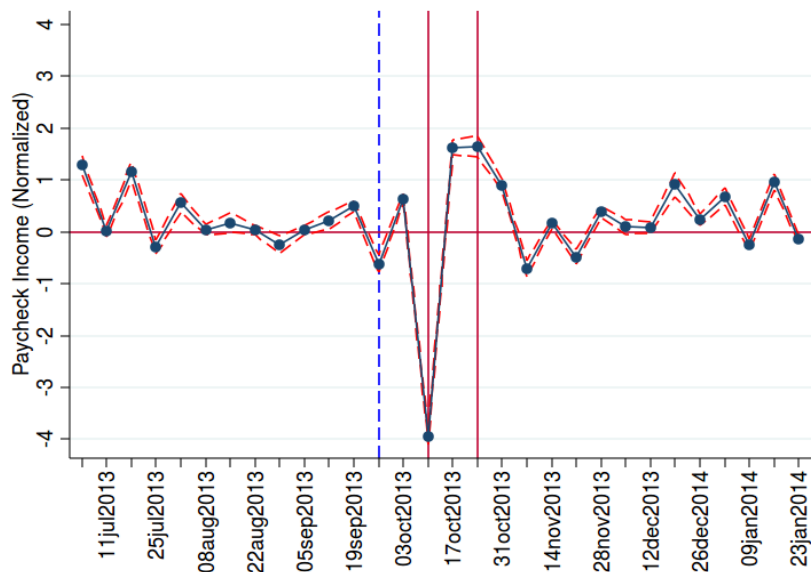
Specification:

LHS = variable of interest (income, category of spending)

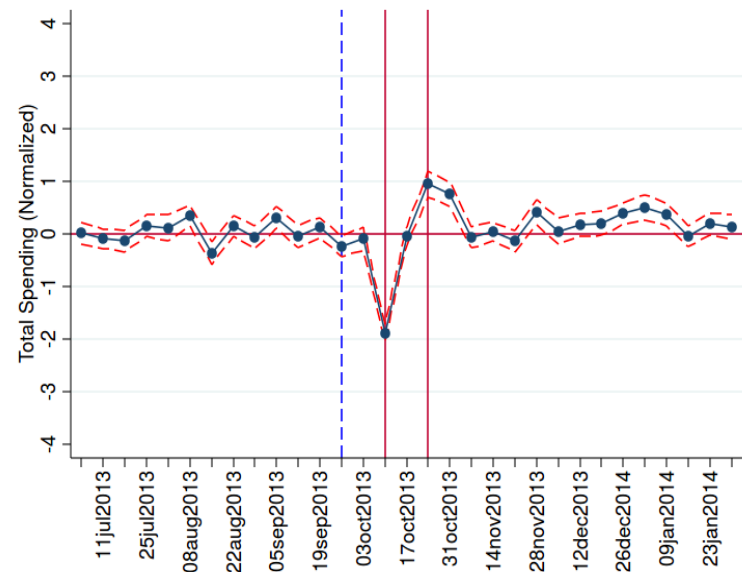
Normalized by average individual spending (daily rate)

Diff-in-diff effects of shutdown

Paycheck income

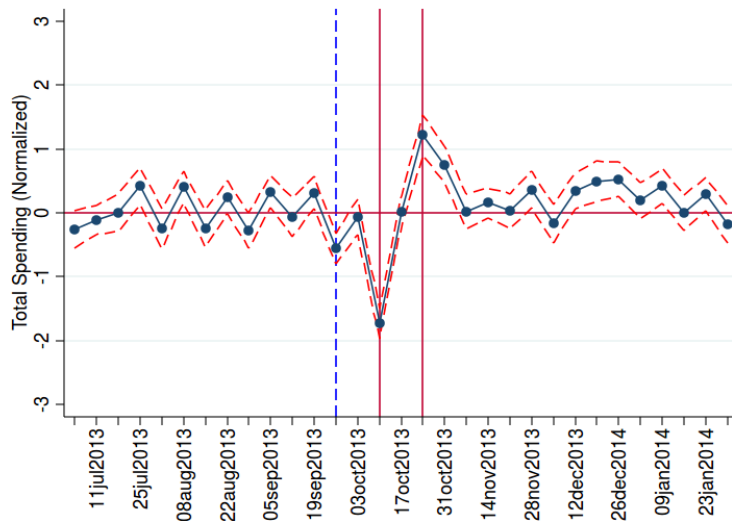


Total spending

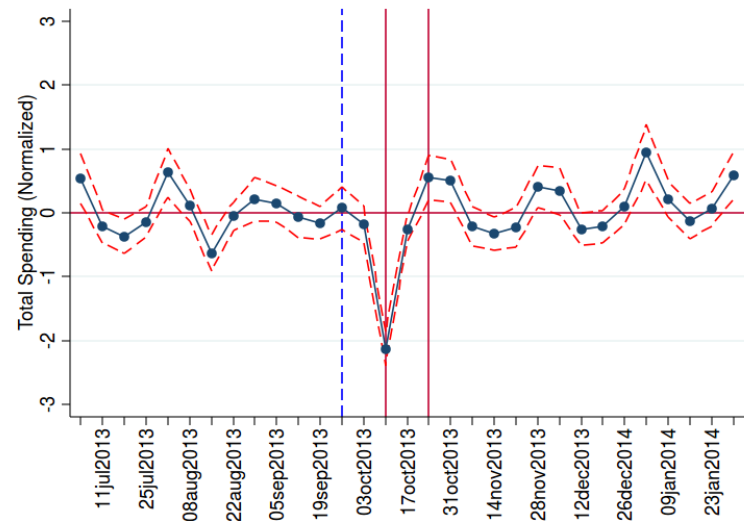


Diff-in-diff effects of shutdown

Non-recurring spending

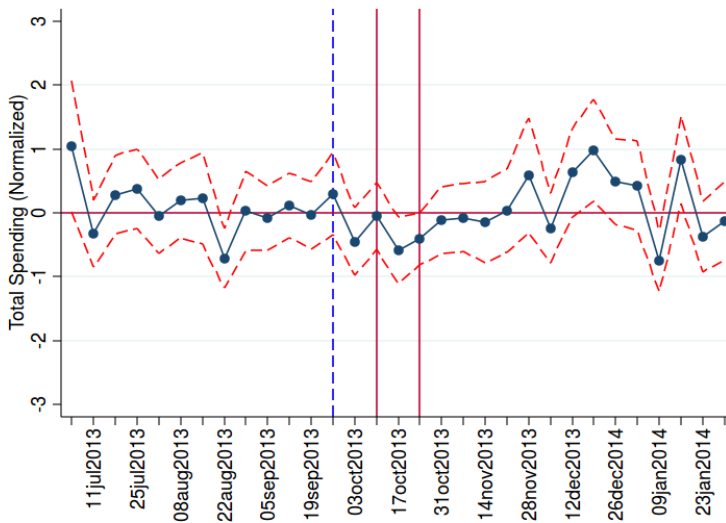


Recurring spending

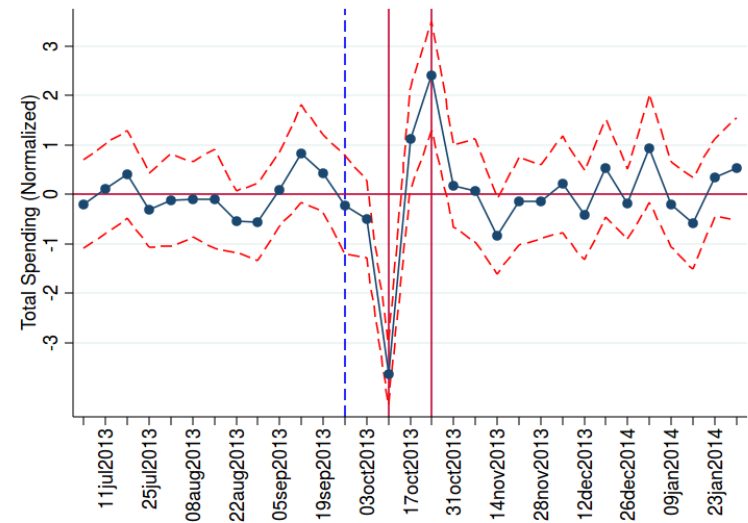


Diff-in-diff effects of shutdown

Credit card spending

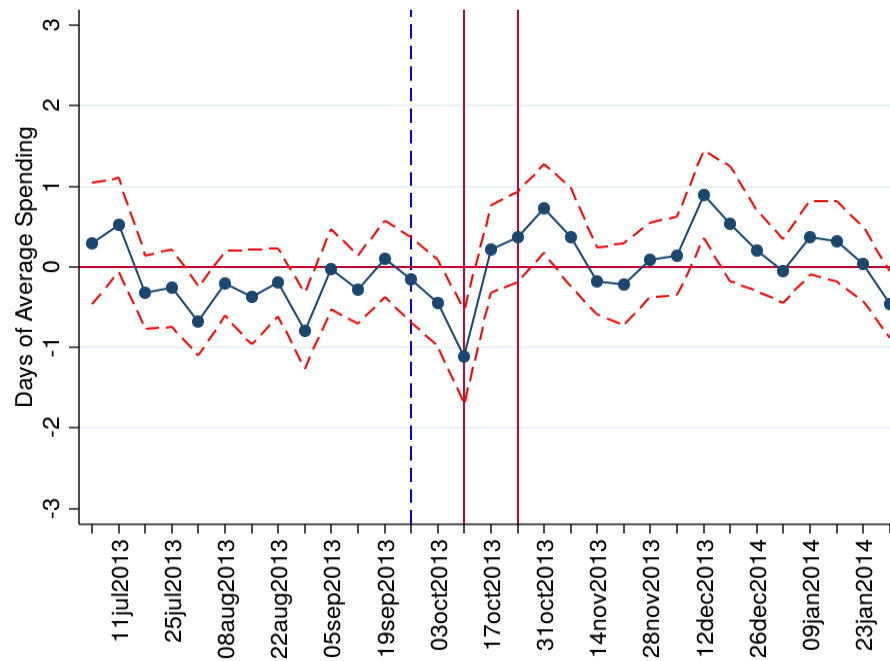


Credit card balance payments



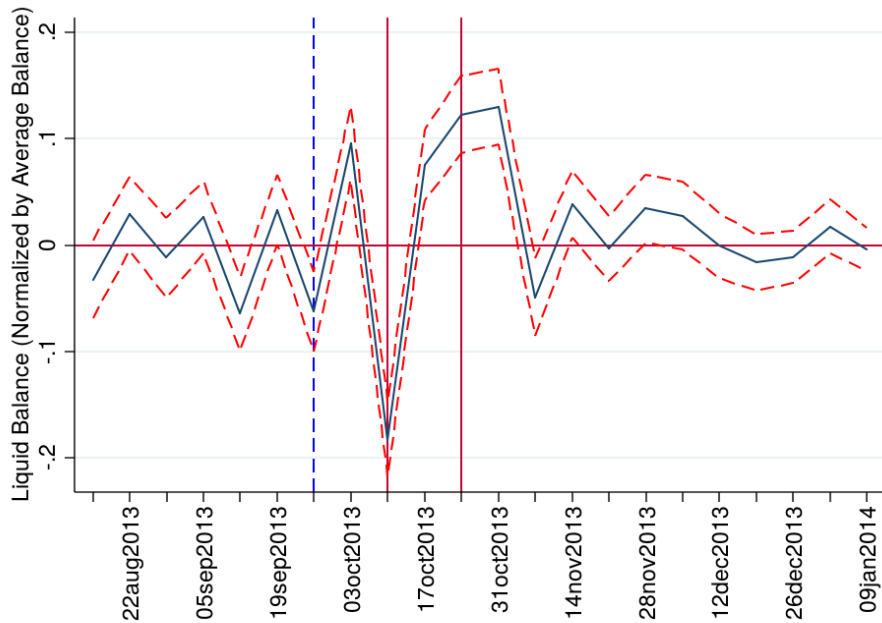
Diff-in-diff effects of shutdown

Coffee shop and fast food

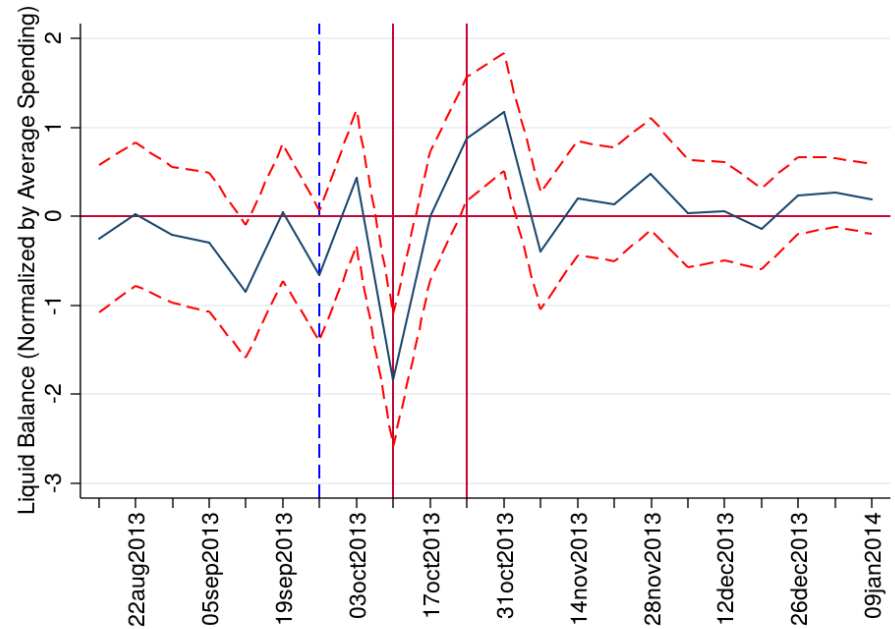


Diff-in-diff effects of shutdown, Liquid Assets

Normalized by Average Liquid Balance

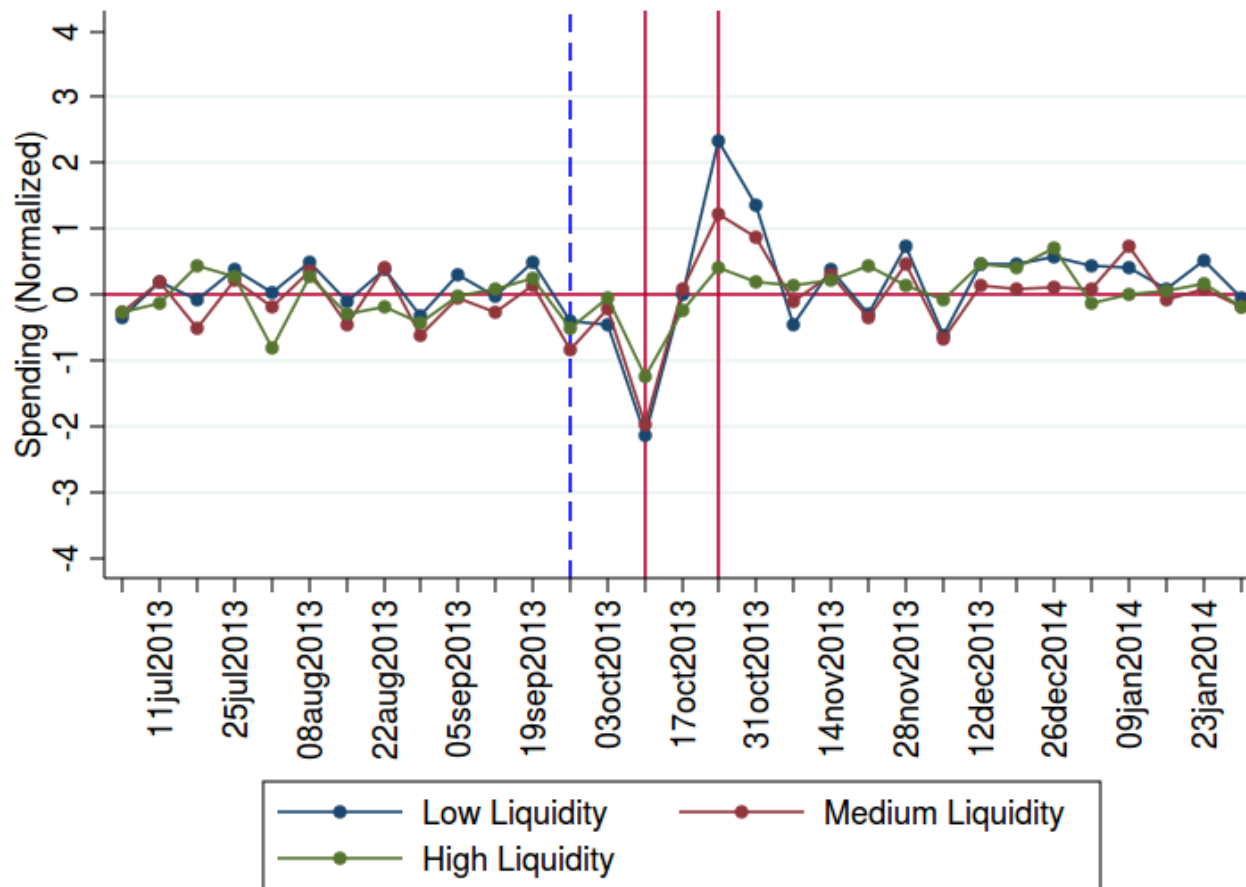


Normalized by Average Daily Spending



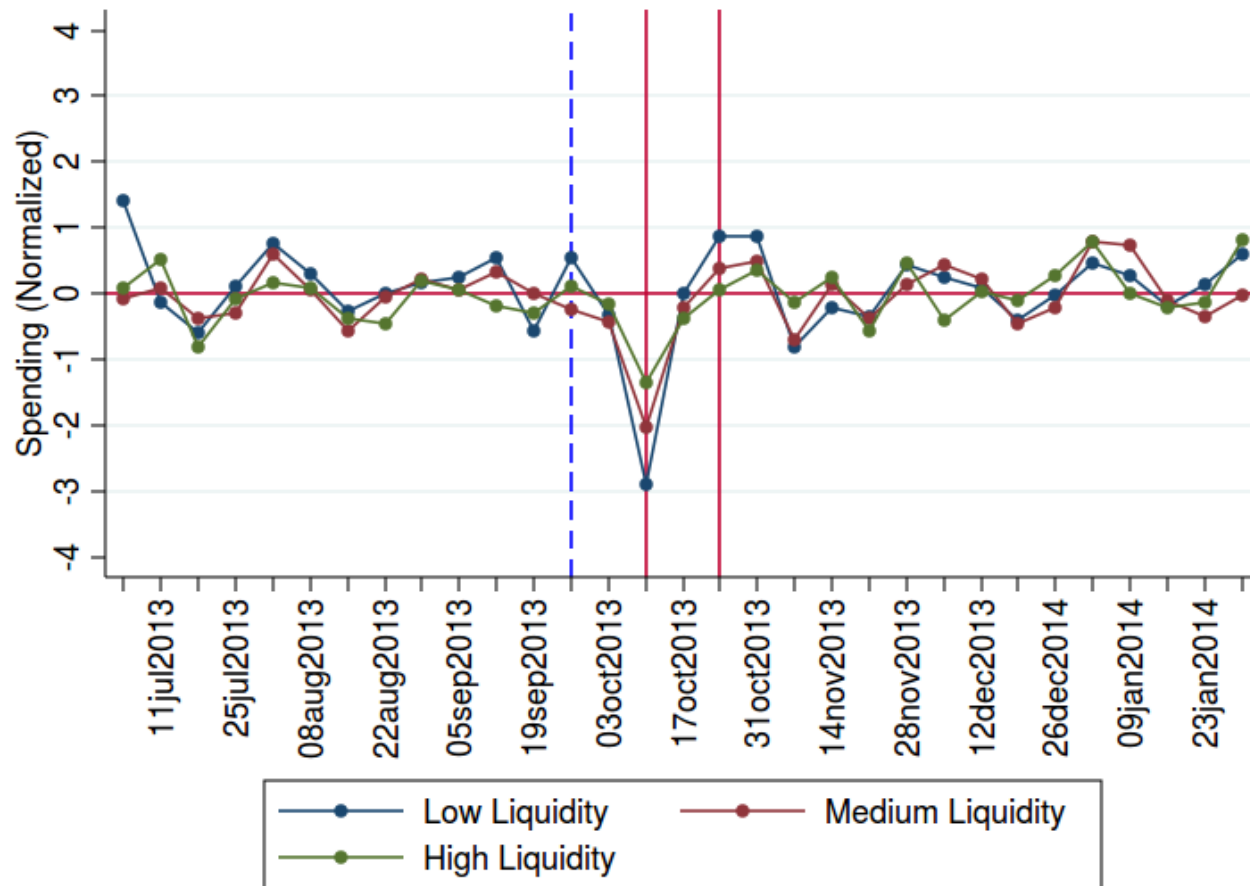
Diff-in-diff effects of shutdown, by liquidity

Non-recurring spending



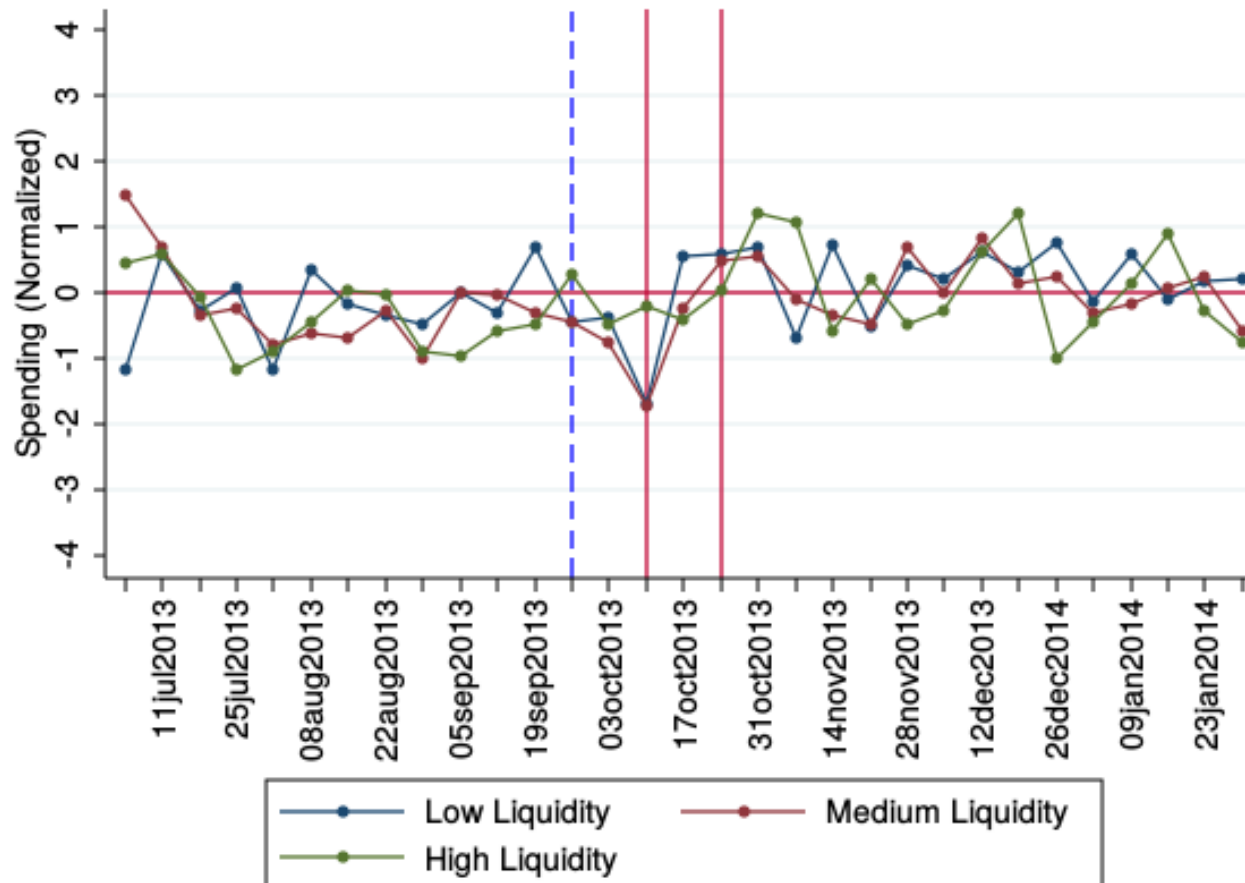
Diff-in-diff effects of shutdown, by liquidity

Recurring spending



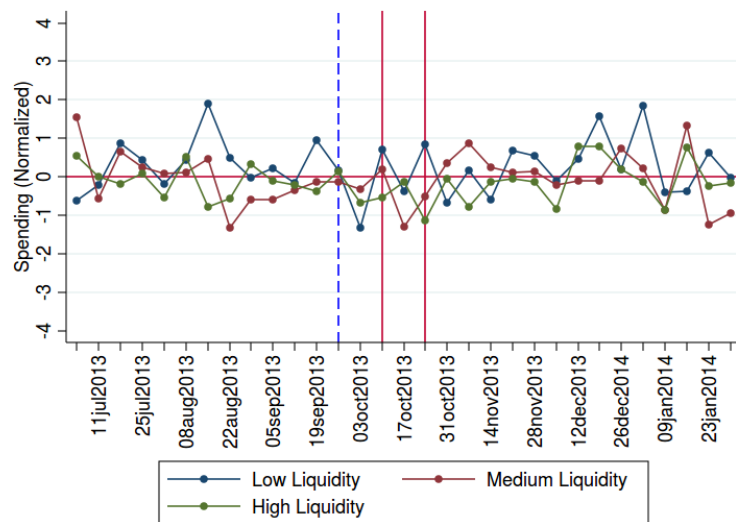
Diff-in-diff effects of shutdown, by liquidity

Coffee shop and fast food

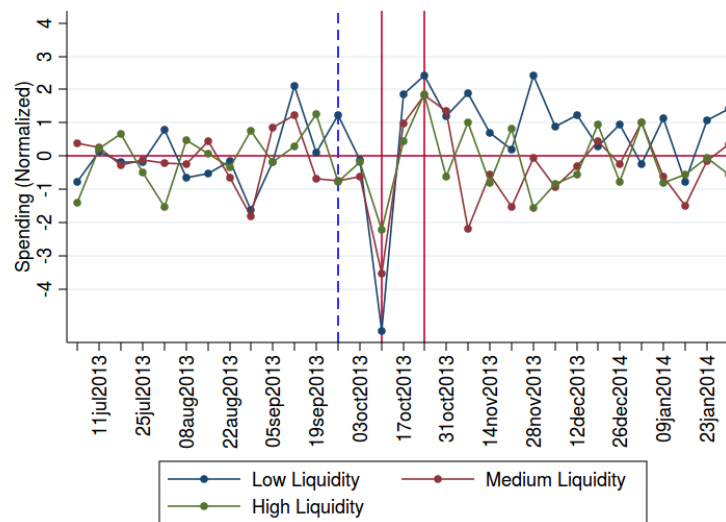


Diff-in-diff effects of shutdown, by liquidity

Credit card spending

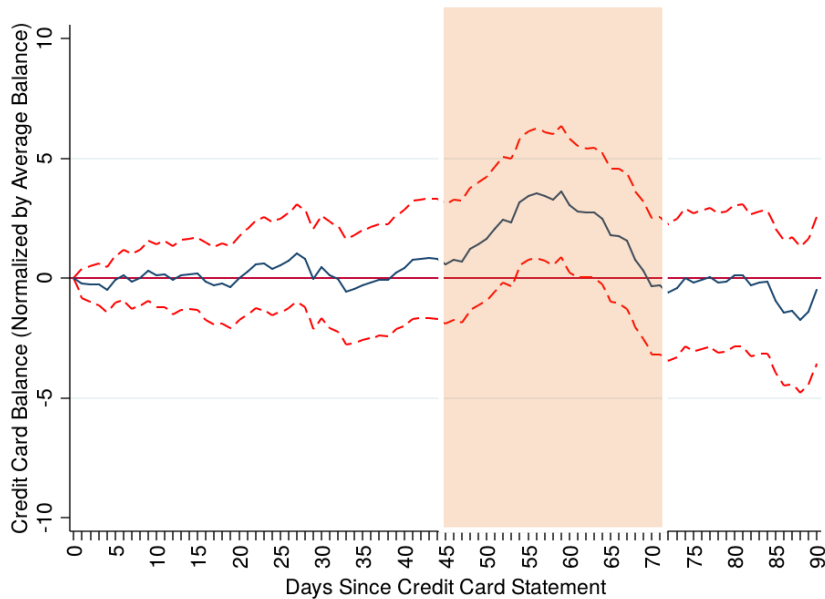


Credit card balance payments

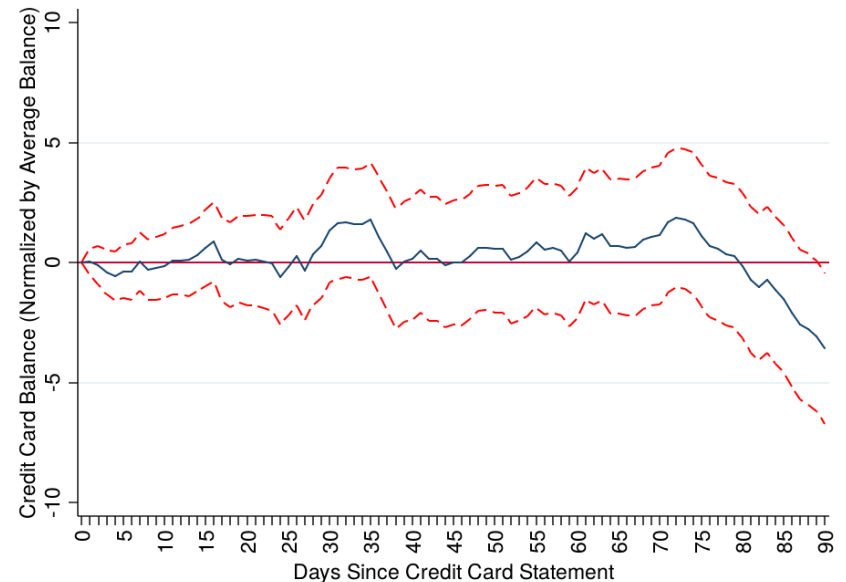


Diff-in-diff effects of shutdown, Credit Card Balance by “Liquidity Risk”

Credit Card Balance,
Accounts at Liquidity Risk



Credit Card Balance,
Accounts Not at Liquidity Risk



- Notes:
- Horizontal axis is days since August 2013
 - Revolvers 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