Discussion of "Tracking the COVID-19 Crisis with High-Resolution Transaction Data"

by Vasco M. Carvalho, Juan R. Garcia, Stephen Hansen, Álvaro Ortiz, Tomasa Rodrigo, José V. Rodríguez Mora, Pep Ruiz

Michaela Pagel – Columbia GSB, NBER, and CEPR

Motivation: A History of Consumption Data

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   - 5.2 Bank account data linked to administrative registries: Andersen et al. (2020)

Benefits of Card Spending Data: Availability and Timeliness

OPPORTUNITY INSIGHTS ECONOMIC TRACKER — HARVARD UNIVERSITY — BROWN

CHOOSE AN INDICATOR

SPENDING	BUSINESSES	EMPLOYMENT	EDUCATION	PUBLIC HEALTH
Consumer Spending	Small Business Revenue	Low-Income Employment	Online Math Participation	COVID Cases
	Small Businesses Open	Low-Income Earnings	Student Progress in Math	COVID Deaths
	Job Postings	Unempl. Claims Rate		COVID Tests
		Unempl. Claims Count		Time Outside Home

SAFEGRAPH | U.S. Consumer Activity During COVID-19 Pandemic

How You Can Get This Data

For academics, non-profits, and governments, we are actively donating SafeGraph data. Hundreds of these collaborators are actively working with SafeGraph data in the COVID-19 Data Consortium; if you are working for the public good, please visit our sign-up page to get involved and get access to free data. Previous researchers have used SafeGraph data to understand coronavirus spread and Starbucks's open-bathroom policy.

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- I will highlight how each of those matter in the analysis of the ongoing Covid-19 pandemic

Current Setting: 2020 COVID-19 Pandemic

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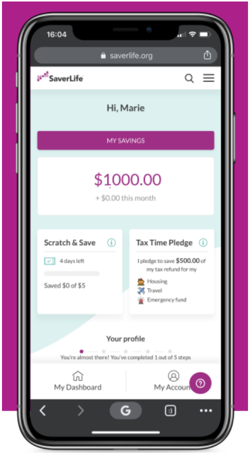
- Starting March 3 in Seattle and March 15 throughout the US, schools and businesses closed or reduced hours
- On March 16, the Federal Reserve announced unprecedented monetary stimulus measures and on March 27 the largest-ever economic stimulus package, the CARES Act, passed

Transaction-Level Bank Account Data

- I use transaction-level data of linked bank accounts from a Non-profit Fintech Company, SaverLife, that works with individuals to increase their savings



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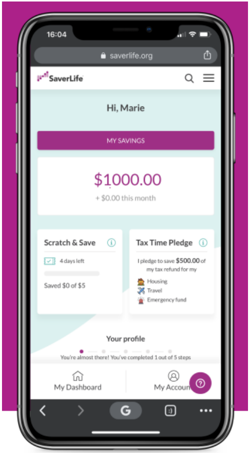

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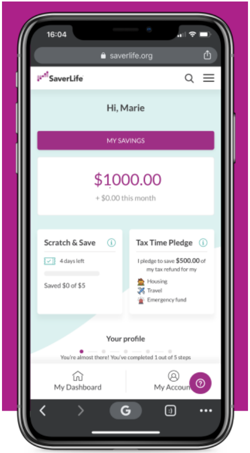

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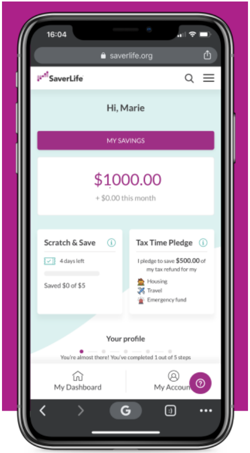
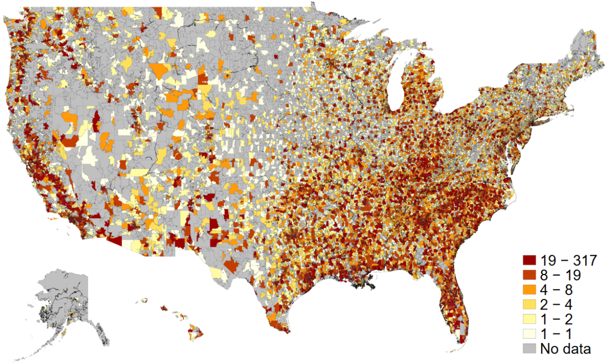
- Let's look at "card spending" to look at challenges 1. to 4.



Data Coverage

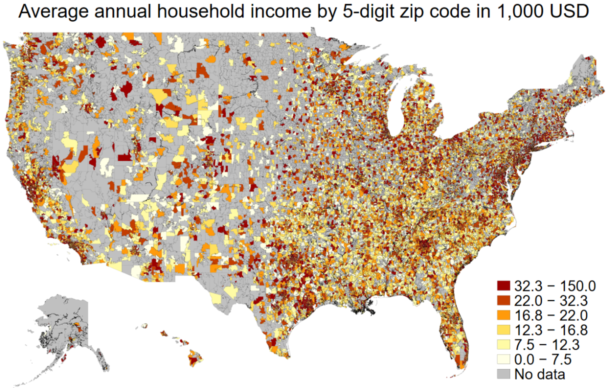
- From August 2016 to July 2020, we observe bank-account transactions for a sample of 84,690 users
- Instead of demeaning at the individual level, we will demean by zip codes: almost the same in this dataset!

Number of users by 5-digit zip code



Two Advantages of Our Data in this Setting

- The Non-profit Fintech targets low-income individuals/households all over the US
- Our data can be updated very frequently (right now, we observe transactions as of July 7th)



Data: Summary Statistics and Comparison to CEX

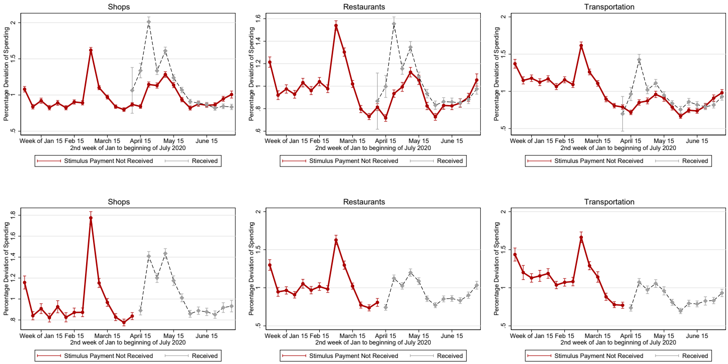
	Mean	Standard Deviation	Percentiles 10%	25%	50%	75%	90%
Age	37.56	11.04	25.00	30.00	35.00	44.00	52.00
Male	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Self-Reported Annual Income	29,993.13	32,651.83	450.00	7,000.00	20,000.00	42,500.00	65,000.00
Number of Linked Accounts	2.26	2.09	1.00	1.00	2.00	2.00	4.00
Number of Transacted Accounts	1.00	0.03	1.00	1.00	1.00	1.00	1.00
Number of Monthly Transactions	87.33	79.61	15.00	36.00	71.00	116.00	172.00
Monthly Payroll Income	1,969.10	3,510.27	2.96	22.39	939.00	2,515.91	4,903.42
Monthly Food Spending	473.36	711.91	38.10	116.49	294.21	610.97	1,096.22
Groceries	251.09	415.19	14.30	41.90	120.67	297.51	615.51
Restaurants	267.29	476.15	23.62	62.64	154.61	326.35	595.59
Pharmacies	53.48	142.38	5.35	11.90	27.74	60.00	116.51
Shopping	498.60	757.39	36.27	109.18	279.26	605.63	1,150.87
Observations	2.30e+07						

Means in the Consumer Expenditure Survey Data

Age	51.09	Monthly Food Spending	708.83
Male	0.47	Groceries	372.01
Annual Income	78,321.16	Restaurants	288.25
Monthly Payroll Income	5,129.75	Shopping	1,178.83

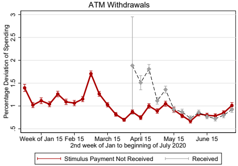
Challenge 1. Spending in Observed Categories

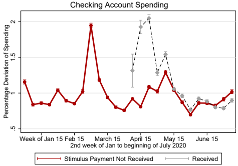
- Spending increased to stockpile home goods and in anticipation of the inability to patronize retailers, then declined sharply, then increased for stimulus check recipients
- Challenge 1. results are quite attenuated when we aggregate to the zip-code level

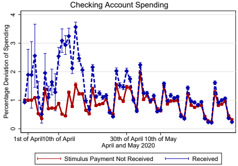


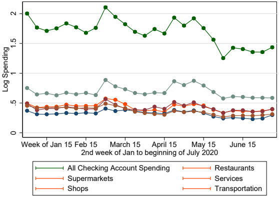
Challenge 2. Spending in Unobserved Categories

- We lose a lot of relevant information when we cannot demean at the individual level
- Challenge 2. shopping, restaurants, services, and transportation is only a small share of all checking account spending



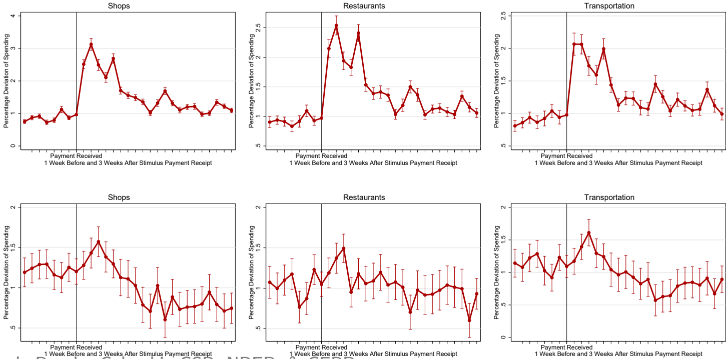






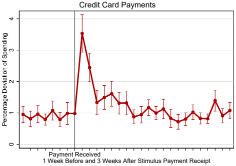
Challenge 1. and 2. Spending in Observed Categories

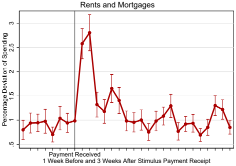
- Spending, especially on non-durables and less so on durables increased substantially in event study design in the few days after stimulus check receipt
- The picture is much less clear when we only know the first date of the stimulus receipt (April 9, 2020)

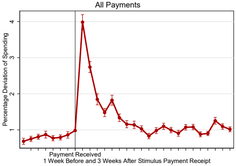


Challenge 3. Spending in Unobserved Categories

- Individuals appear to have delayed bill and rent payments and catch up with the funds from the stimulus checks
- We cannot see that in card spending data, but it is very important to evaluate the fiscal multiplier effects of the stimulus payments

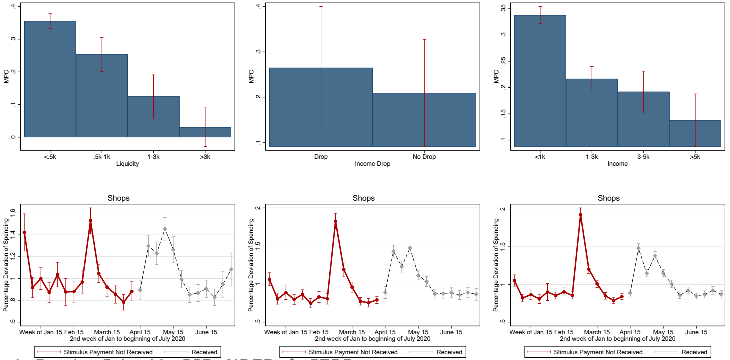






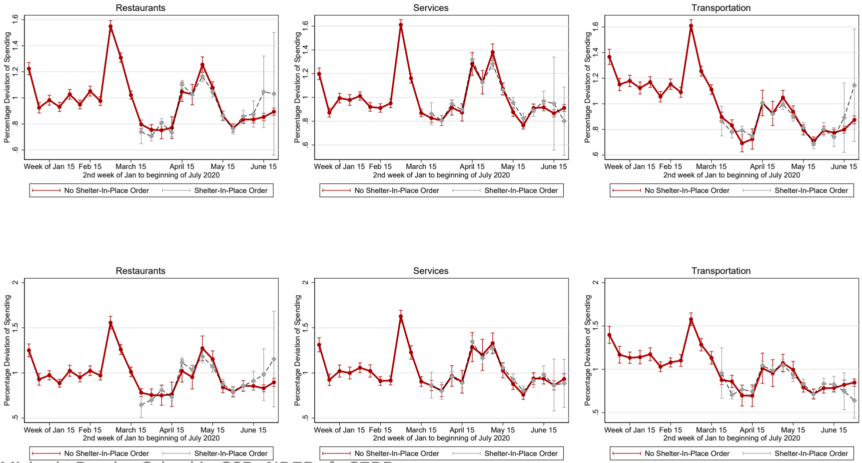
Heterogeneity In Observed Categories by Zip-Code Level Income

- Largest increases by individuals with low account balances in the beginning of April (less heterogeneity by income drops or levels)
- And this is poorly approximated by time-invariant zip-code level income



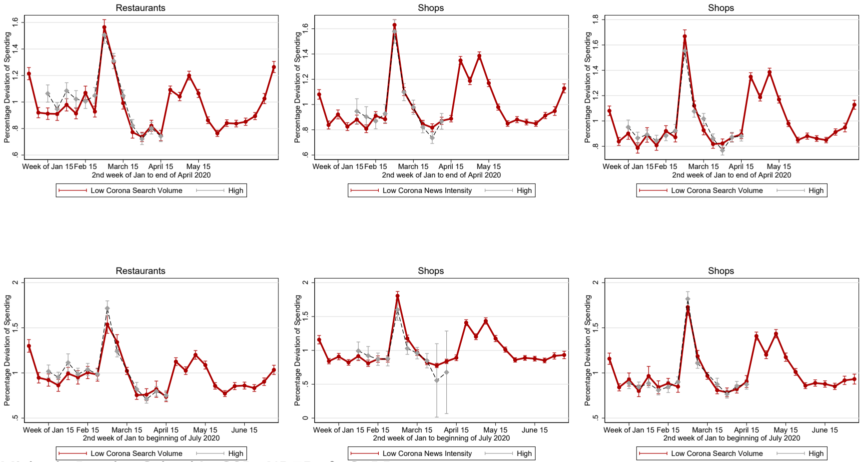
Challenge 3. Heterogeneity

- Not easy to find in state differences
- Shelter-in-place orders versus not are difficult to find in individual-level data with individual fixed effects



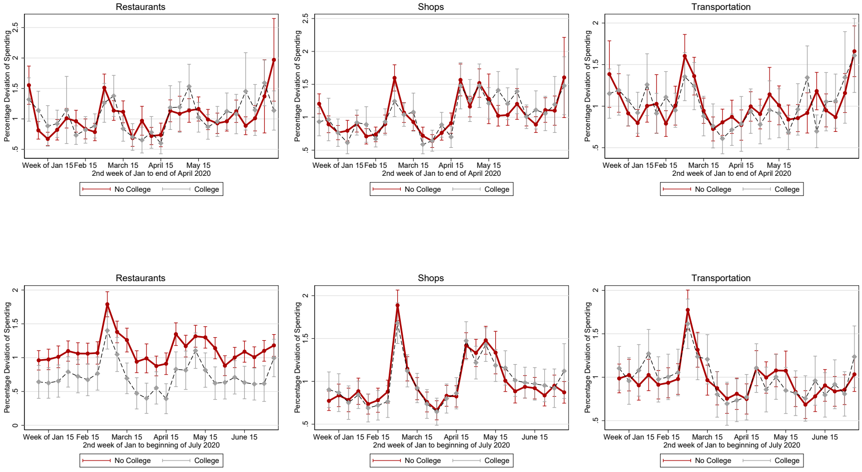
Challenge 3. Heterogeneity

- What about news intensity?
- Timeline trend is consistent (Corona search volume is a leading indicator of news intensity)



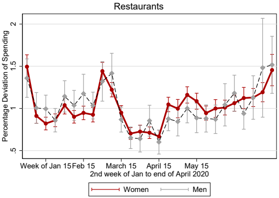
Challenge 3. Heterogeneity: Where There is None

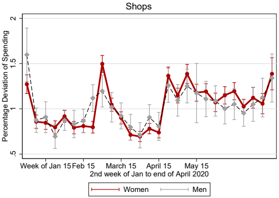
- Sometimes we see differences in aggregate data that we cannot find in individual-level data

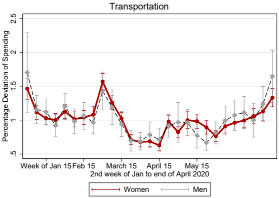


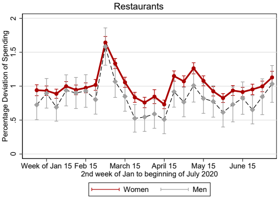
Challenge 3. Heterogeneity: Where There is None

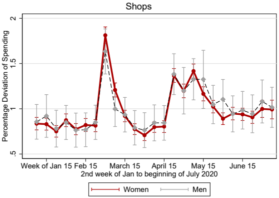
- But not always tightly estimated

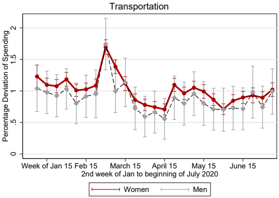












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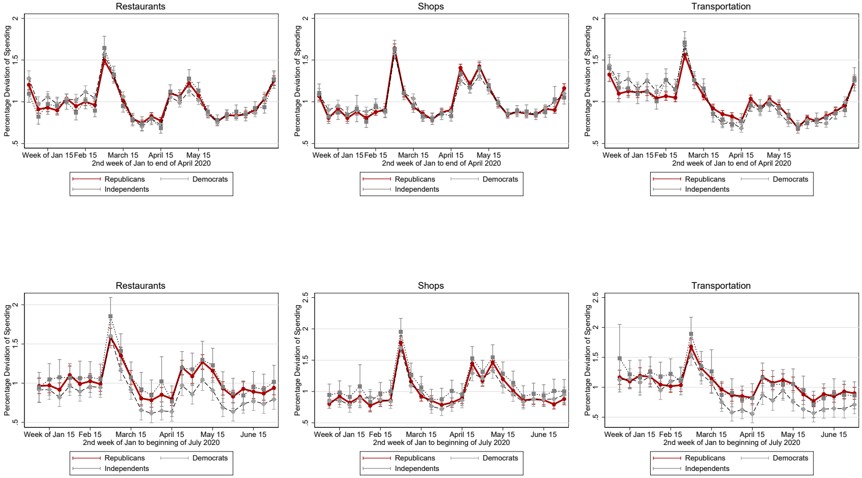
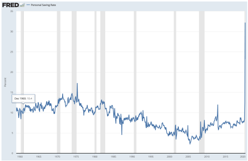
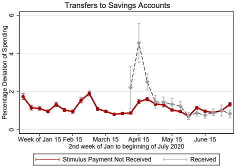
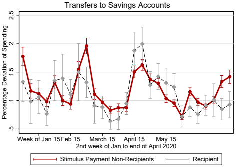


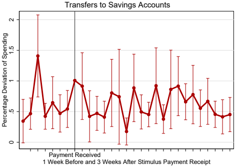
Challenge 4. Balance Sheet Results: Savings

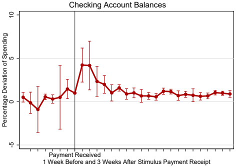
- In BEA/NIPA data, there was a massive increase in the personal savings rate but we find some mixed evidence there





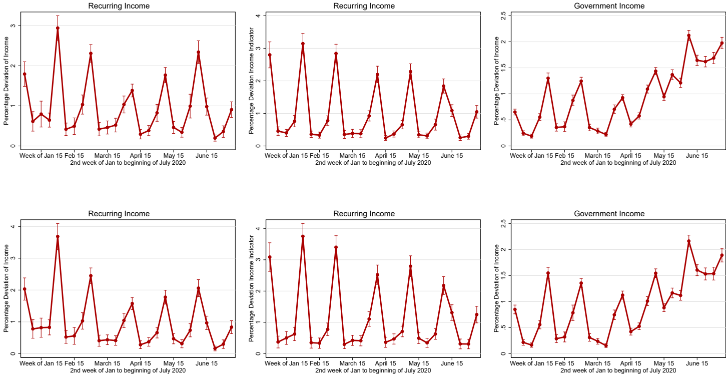






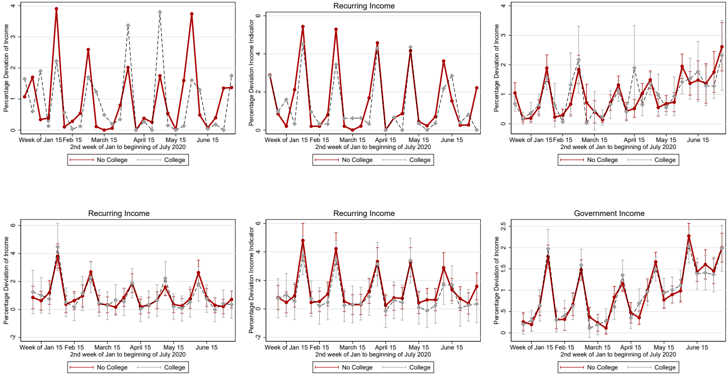
Challenge 4. Income in the Aggregate

- We see decreases in the amount and likelihood of payroll and other recurring income as well as increases in government income: indistinguishable



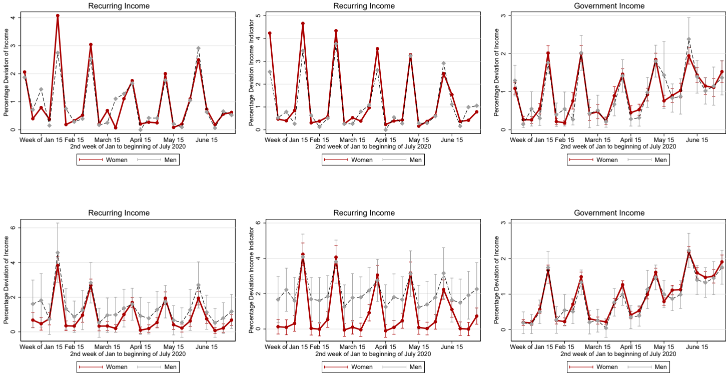
Challenge 3. and 4. Heterogeneity: Differences by Education

- College educated users experienced less decreases in the amounts and likelihood of recurring income: individual-level differences are masked in aggregated data



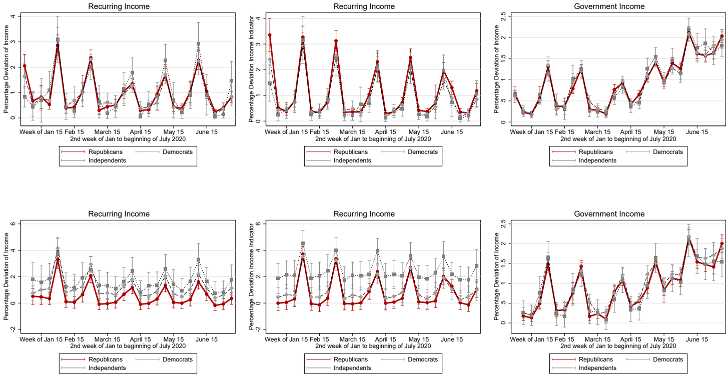
Challenge 3. and 4. Heterogeneity: Differences by Gender

- Men experienced less decreases in the amounts and likelihood of recurring income: individual-level differences are masked



Challenge 3. and 4. Heterogeneity: Differences by Partisanship

- Heterogeneity where there is none, but not very tightly estimated



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* I thank the CBS Fintech Initiative for providing access to the data used here

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