Crowding out crowd support?
Substitution between formal and informal insurance

Kyle Coombs

Columbia University

September 25, 2024

Person-to-person informal support during unemployment spells

- The unemployed rely on informal support
- P2P platforms facilitate informal transfers

The New York Times

When We Were Socially Distant, Money Brought Us Closer

Feb. 19, 2022

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WSJ

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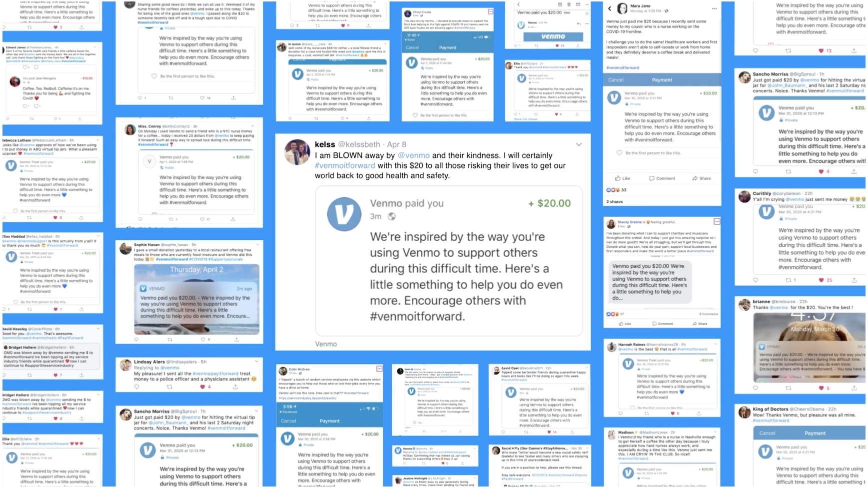
A New Way to Donate to the Needy in the U.S.: Venmo Cash Directly

Digital cash transfers have surged during the pandemic, providing help to those struggling to make ends meet, but are such payments effective?

VenmoItForward Campaign Spring 2021



Person-to-person informal support during unemployment spells

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- Researchers can track digital transfers

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- UI pools risk widely, but can be insufficient

'I Cry Night and Day': How It Took One Woman 8 Weeks to Get Unemployment

Nadine Josephs has not worked since March 13. Trying to get benefits from New York became a full-time job.

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- Researchers can track digital transfers
- UI pools risk widely, but can be insufficient
- Is UI crowding out informal support?

'I Cry Night and Day': How It Took One Woman 8 Weeks to Get Unemployment

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Outline of talk

Questions

- To what extent do people receive cash payments via P2P platforms after job losses?
- Does UI crowd-out informal insurance via P2P?
- If so, what are the welfare consequences?

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Questions

- To what extent do people receive cash payments via P2P platforms after job losses?
  - Small, but targeted
- Does UI crowd-out informal insurance via P2P?
  - Hardly
- If so, what are the welfare consequences?
  - Negligible

This Project

- Categorize earnings, UI, P2P flows, and spending in a new transactions-level data set with over $2.5M$ mostly low-wage workers including a large sample of UI recipients ($N \approx 300K$)
- Track P2P inflows and outflows using within-person event studies around job losses
- Assess targeting with heterogeneity analysis by economic and demographic characteristics
- Estimate crowd-out by UI with IV-DID using three pandemic natural experiments

Preview of Findings

- P2P inflow increases peak at \$30 in month after job loss, and \$175 cumulatively
- Limited by network income: Users with low-income networks get \$125 cumulatively
- Targeted: Single mothers get over \$500 cumulatively, independent of network income
- Crowd-out estimates show P2P inflows fall (at most) \$0.04 for a \$1 increase in UI
  - First such estimates in a high-income country outside a lab setting
  - Negligible welfare consequences, unless informal insurance market is larger than formal market

Literature

- Extent that public insurance crowds out private insurance can change welfare calculation
    - Chetty and Saez (2010), Baily (1978), Di Tella and MacCulloch (2002), Lin et al. (2014)
- Administrative data analysis finds large consumption responses to job loss and UI receipt with low job finding responses to UI expiration
    - Farber et al. (2015), Ganong and Noel (2019), Card et al. (2015), and Johnston and Mas (2018)
    - **Pandemic specific**: Ganong et al. (2022), Farrell et al. (2020), Coombs et al. (2021)
- Low-income economies rely on informal credit and gifts to income pool
    - Townsend (1995), Kinnan and Townsend (2012), Chiappori et al. (2014), Carranza et al. (2021), Auriol et al. (2020), Angelucci and De Giorgi (2009)
    - **Mixed crowd-out evidence**: Banerjee et al. (2022), Jensen and Richter (2004), Huang and Zhang (2021), Albarran and Attanasio (2003), Takahashi et al. (2019), Strupat and Klohn (2018), Gerardi and Tsai (2014)
- P2P platforms lower transaction costs and facilitate income pooling
    - Jack and Suri (2014), Balyuk and Williams (2021)

Transactions Dataset: Earnin

- Earnin is a financial-management app that provides pay advances (and other products) to users that link bank accounts
- Largely low-wage, representative of workers affected by widespread economic disruptions
  - Full dataset includes 0.7 percent of 30M UI recipients in US in July 2020
- Surveys in August 2020 and 2021 on demographics, expectations, and preferences

Map of UI coverage | CPS vs. Earnin Earnings | Synthetic Panel Construction | Survey Design

Categorizing transactions into earnings, UI, P2P, and spending

- Use following information to categorize transactions:
  1. Bank memo
  2. Transaction amount
  3. Transaction date
  4. Earnin-provided earnings flag and transaction groups
- Initially categorize using groups and regular expression searches of memos
- Restrict P2P flows based on dollar value, date, or link to earnings, sales, or taxes
- Algorithm flags earnings using within- and across-user information Earnings Algorithm
  - Unemployment spells start with last paycheck before five weeks without any paycheck
  - UI spells start with first deposit after three weeks without any deposit

Coverage Map | Spell Lengths | Low UI take-up rate | P2P flagging rules

Analysis Sample

- Restrict to an analysis sample:
  - Keep users with 5+ outflows per month that are continuously employed through June 2019
  - Treated: Have at least one job loss between July 2019 and September 2020 (130,502 users)
  - "Not yet treated": Users with first job loss in September 2021 and no prior UI (4,245 users)
- Sample of 134,747 users aggregated at the monthly level
- UI analysis: drop seven states with poor UI tracking for 108,181 users – 51,850 receive UI

False Negatives | Sample Counts | UI receipt by treatment cross tabs | Good state coverage | Analysis sample: Good state coverage

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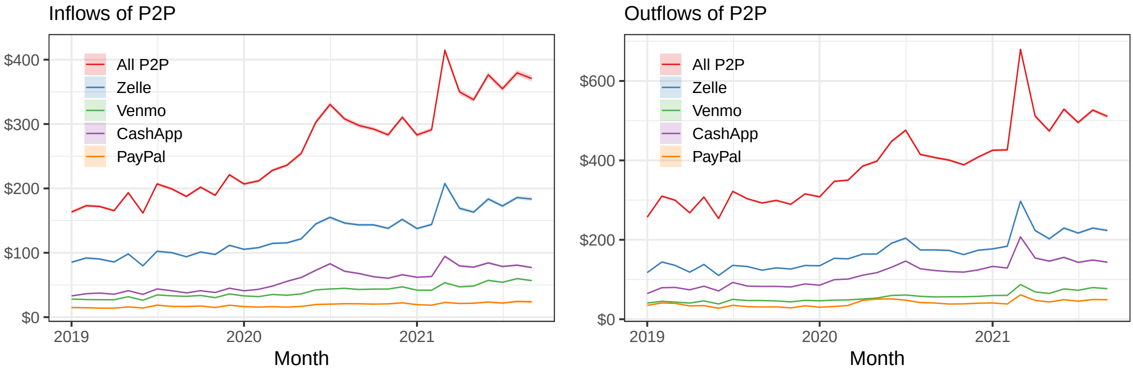
P2P flows have increased across platforms



(a) Inflows (b) Outflows

Notes: P2P inflows and outflows over sample period. Transactions flagged if memos contain P2P-related regular expressions or transaction group is a P2P platform. Dollar amounts between $5 and $15,000 and memos not linked to purchases, informal earnings, gig platforms, or stimulus payments.

What makes up insurance and P2P?

Forms of insurance

- Formal unemployment insurance
- Assets
- **Informal insurance (e.g., from community)**

Types of informal insurance

- In-kind support (e.g., groceries, moving in)
- Intrahousehold Reallocation (e.g., spousal labor supply)
- **Money from friends**

Makeup of P2P

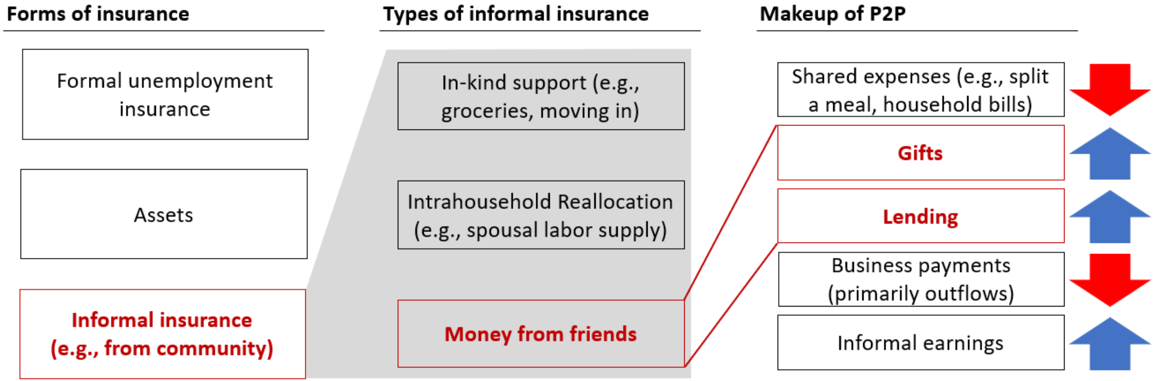
- Shared expenses (e.g., split a meal, household bills)
- **Gifts**
- **Lending**
- Business payments (primarily outflows)
- Informal earnings

Assumption: changes in P2P proxy for cash & checks

- P2P is replacing cash and checks in informal transactions, accelerated by pandemic
  - Cash is infeasible to track at a high frequency
  - Earnin users more likely to use digital payment platforms
- For crowd-out, I care about the slope and not the level
- P2P lowers fixed costs, expanding informal insurance networks (Jack and Suri, 2014)
- Difference in slope for cash/checks vs. P2P is ambiguous due to composition:
  - P2P networks have more marginal members, suggesting P2P crowded out more
  - If cash givers have better info about personal finances, P2P may be crowded out less

Jack and Suri (2014) Welfare | DCPC instruments | DCPC instrument by purpose | DCPC vs. Earnin amount shares | DCPC vs. Earnin count shares

What makes up insurance and P2P?



Notes: Arrows indicate expected changes after job loss. To isolate informal insurance within P2P, I omit transactions with memos that mention sales, taxes, gig platforms, or other earnings. Results are robust to including these transactions.

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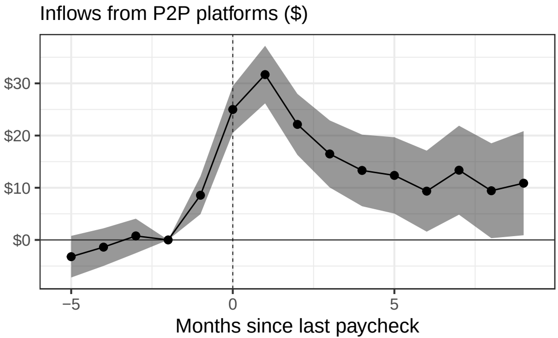
Within-person event study to measure excess P2P

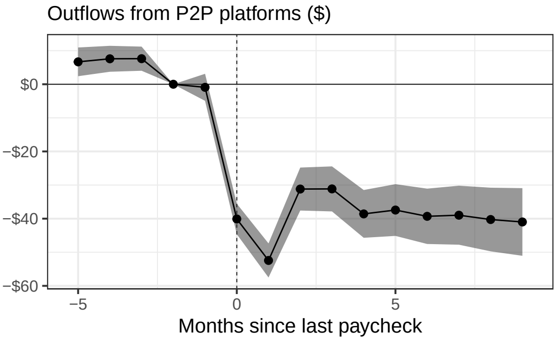
$$
\begin{aligned}
y_{it} = \alpha_i + \lambda_t + \beta_{-6} \sum_{s \leq -6} D_{it}^s + \sum_{s \in [-5,-3]} \beta_s D_{it}^s + \sum_{s \in [-1,9]} \beta_s D_{it}^s + \beta_{10} \sum_{s \geq 10} D_{it}^s + \varepsilon_{it} \\
y_{it} : \text{ any outcome} \\
\alpha_i : \text{ individual fixed effect} \\
\lambda_t : \text{ month fixed effect} \\
D_{it}^s : \text{indicator for } s \text{ time periods relative to } i \text{ becoming unemployed at } s = 0
\end{aligned} \tag{1}
$$

- Omit two months prior to becoming unemployed due to anticipation effects
- For heterogeneity analysis: interact a group indicator G_{it} with D_{it}^s

P2P inflows and outflows after unemployment



(a) Inflows

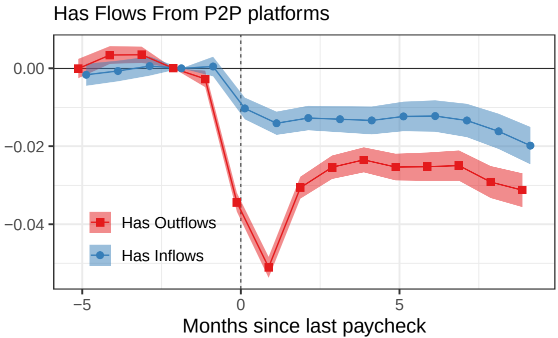


(b) Outflows

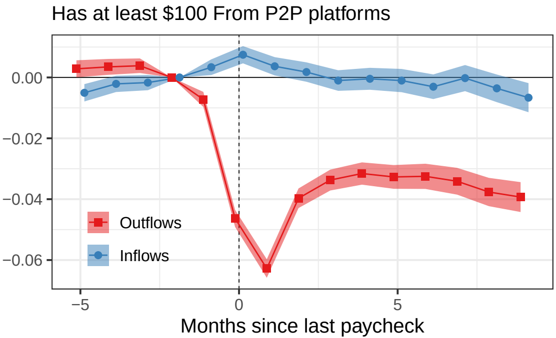
Notes: Event studies of P2P inflows and outflows around job loss.

Conditional on prior use | By Platform | By Year | Gardner | Spell length | NAICS code | Number of spells | Gig Work | Informal P2P Earnings | P2P Replacement Rate | Risk Aversion | Net P2P Earnings | Net P2P Income

Extensive Margin: Using P2P?



(a) $\mathbb{P}(P2P > \$0)$



(b) $\mathbb{P}(P2P > \$100)$

Notes: Whether user has any P2P inflows or outflows in a month.

By Platform | By Platform ($100) | Gig Work | UI receipt | UI receipt ($100) | Divisible by $25 | Transaction size

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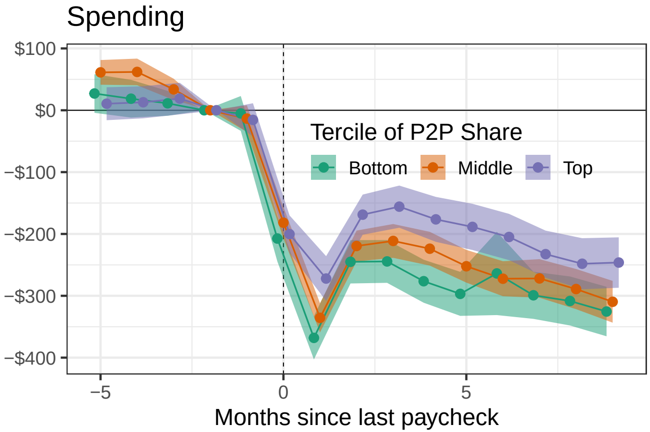
Active users of P2P smooth consumption more



Notes: Event study coefficients are interacted with indicators for the tercile of median monthly share of flows linked to P2P more than three months before job loss.

"Active" measurement | P2P inflows | P2P inflows 3+ months

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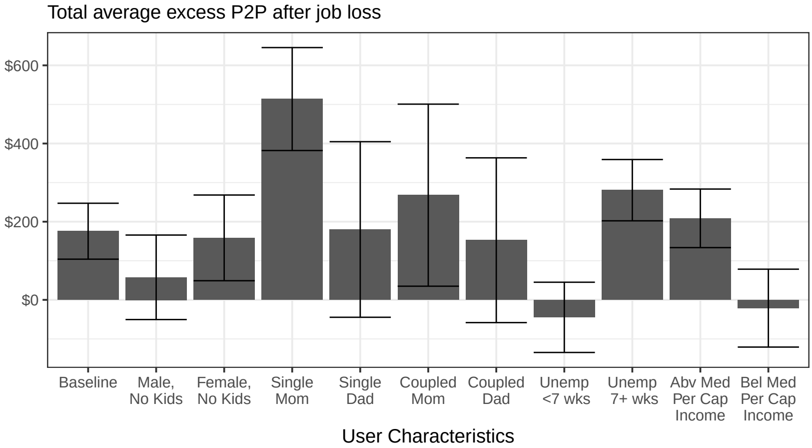
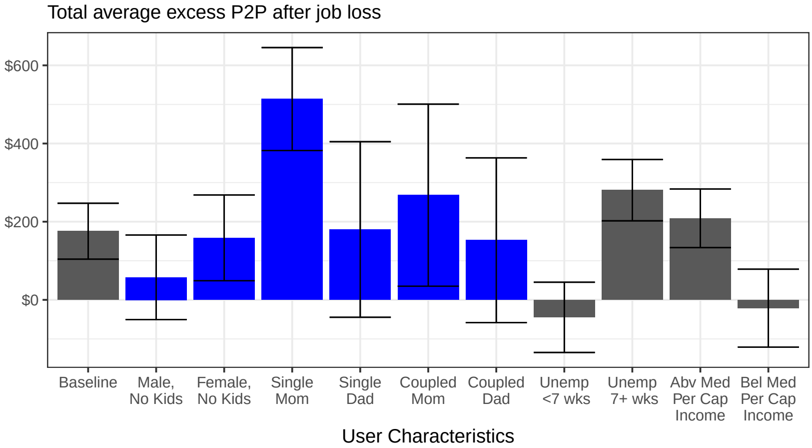
Heterogeneity in cumulative support



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months −1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

Replacement Rate | Race & Ethnicity | Race & Ethnicity RR

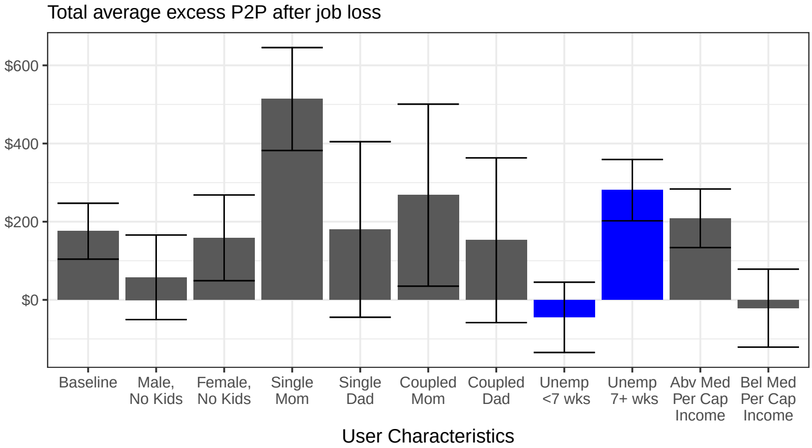
Single mothers targeted



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months −1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

Replacement Rate | Gender, parent, relationship | Race & Ethnicity | Race & Ethnicity RR

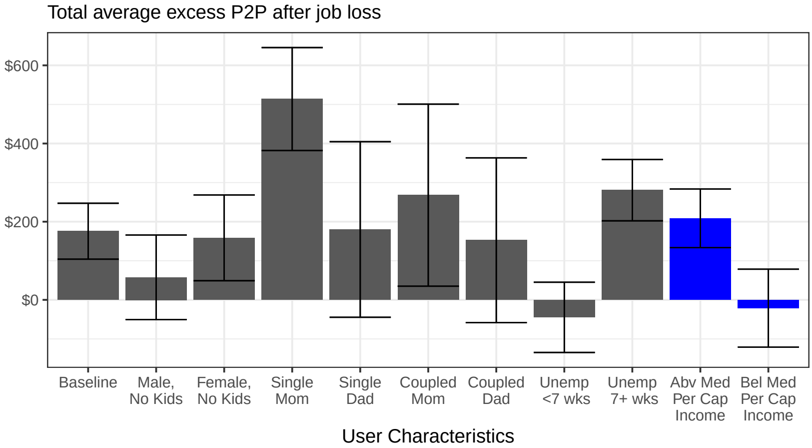
Long-term unemployed targeted



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

Replacement Rate | Spell length | Race & Ethnicity | Race & Ethnicity RR

Users in low-income counties get $0 support



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

Replacement Rate | ACS PCI | Race & Ethnicity | Race & Ethnicity RR

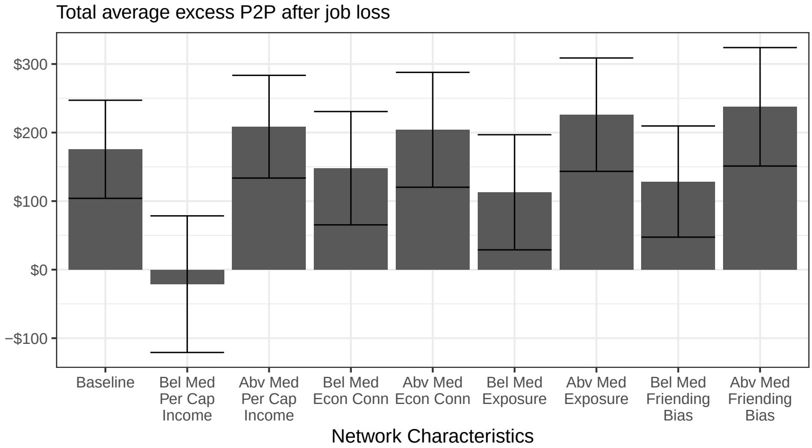
Social Capital Atlas: Economic connectedness of observed social networks

- Social networks are not coterminous with geography in the US
- Chetty et al. (2022) use Facebook data to create three measures cross-socioeconomic status (SES) friendships within social networks, aggregated to the zip code level:
  1. **Economic Connectedness**: Share of high-SES friends among low-SES people
  2. **Exposure**: Share of high-SES people within a network
  3. **Friending bias**: Rate low-SES people befriend[1] high-SES people within a group

Decomposition | Exposure Map | Friending Bias Map | Economic Connectedness Event Study | Exposure Event Study | Friending Bias Event Study

[1] Chetty et al. (2022) define friending bias as preference for low-SES friendships. I reverse this, so results are consistent across each measure.

Economic connectedness associated with smaller gap in support



Notes: Cumulative excess P2P informal support after job loss calculated as the sum of event study coefficients for relative months −1 through 10 interacted with the relevant group shown on the x-axis.

Replacement Rates | Parent by Econ. Con. | Parent by Econ. Con. Rep. Rate | Parent by ACS PCI | Parent by ACS PCI Rep. Rate

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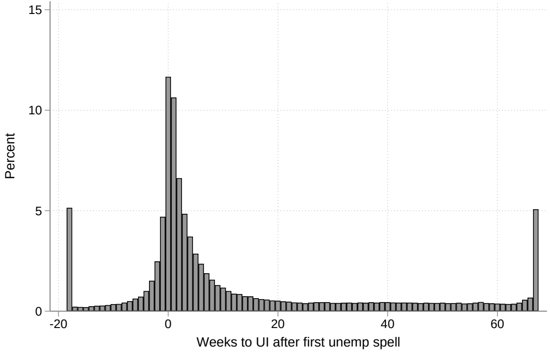
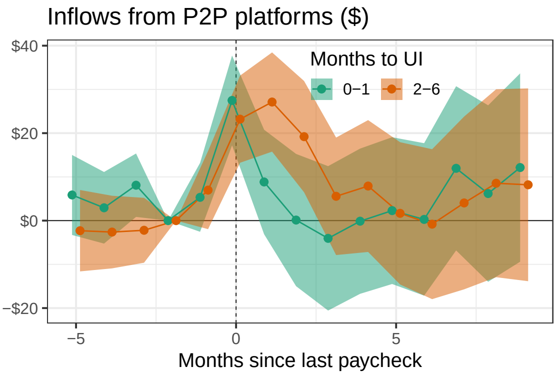
UI delays are common



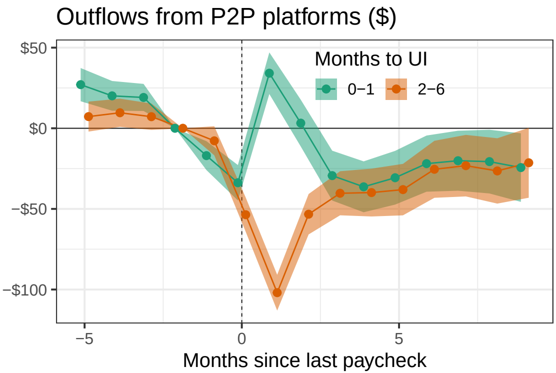
Notes: Weeks to nearest UI spell after first job loss.

- UI delays are common especially in 2020
- Does P2P fill in the gaps?
- Break into cohorts receiving UI 0-1 months or 2-6 months after job loss

Later UI recipients receive inflows for longer horizon



(a) Inflows



(b) Outflows

Notes: Event studies of inflows and outflows where coefficients are interacted with months to receiving unemployment insurance.

UI receipt interaction | UI subsample split | User Replacement Rate | State Replacement Rate

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Quasiexogenous variation in UI from pandemic policy changes

Follow Ganong et al. (2022), Coombs et al. (2021) to isolate variation in UI from pandemic:

1. Delayed UI receipt driven by overload of applications in March 2020
2. July 2020 expiration of $600/week in Federal Pandemic Unemployment Compensation
3. June 2021 early withdrawal from federal $300/week in UI benefits by 19 states

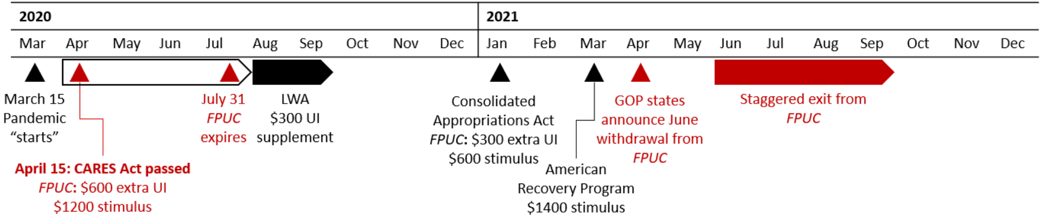

Figure: Timeline of legislative changes to UI and stimulus payments during the pandemic

UI Claims | March 2020 Treatment Assignment | July 2020 Treatment Assignment | June 2021 Treatment Assignment

IV Difference-in-differences to measure crowd-out

Look at one month before and one month after each relevant policy, r captures crowd-out

$$\begin{aligned} \text{P2P}_{it} &= r\hat{\text{UI}}_{it} + \lambda_i + \lambda_t + \epsilon_{it} \\ \text{UI}_{it} &= \beta \text{Treat}_{it} \times (\text{Post Month})_{it} + \alpha_i + \alpha_t + \nu_{it} \end{aligned}$$

where Treat_{it} is an indicator for being in the relevant treated group

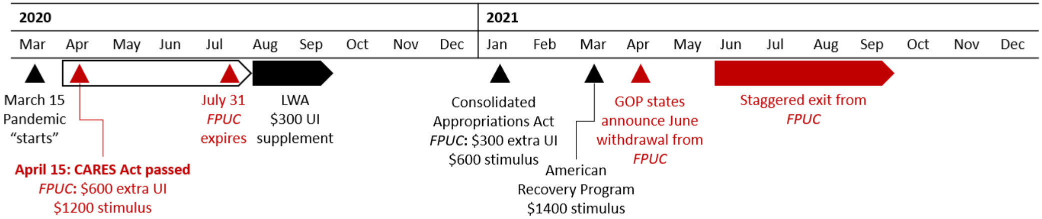

Figure: Timeline of legislative changes to UI and stimulus payments during the pandemic

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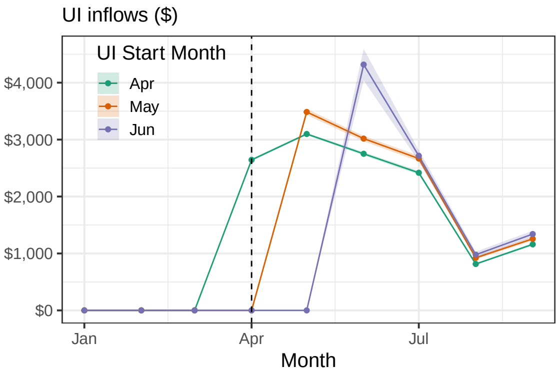
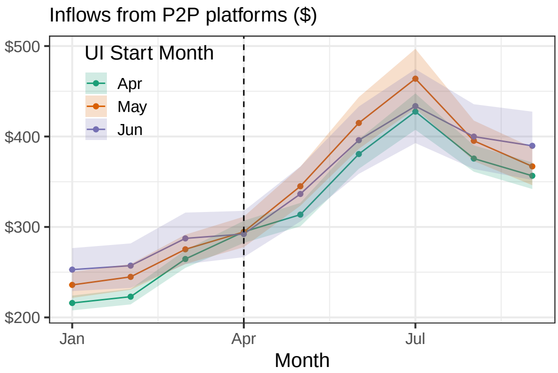
Experiment 1: March Job Loser UI Receipt Cohorts



(a) UI Inflows

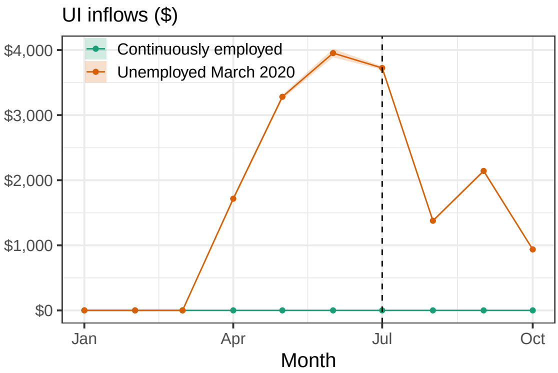


(b) Inflows

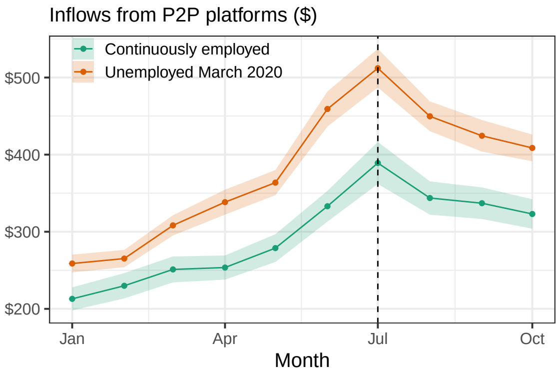
Notes: Subset of users that became unemployed in March by month they receive UI. Treated group are April UI recipients, control group are June UI recipients. IV-DID compares March and May.

Treatment Assignment Spending/Outflows

Experiment 2: March job losers, insured vs. Employed through Dec 2020



(a) UI Inflows

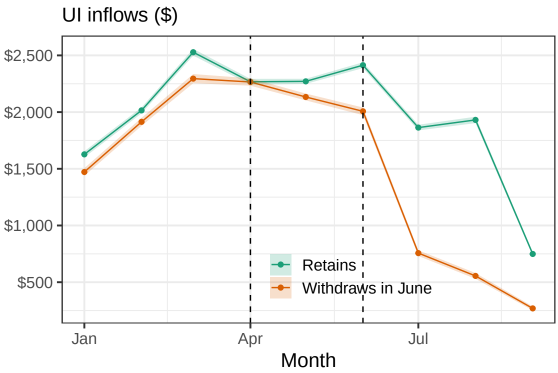


(b) P2P Inflows

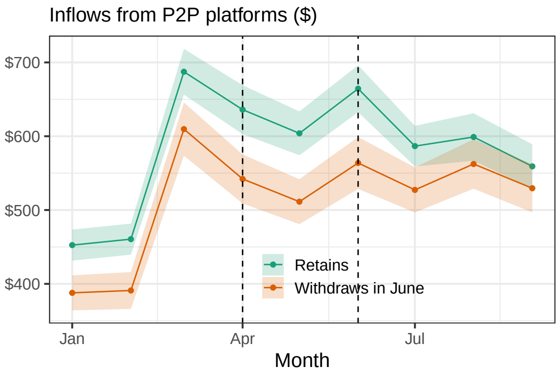
Notes: Treatment group are those unemployed in March and insured by June. Control group are those unemployed after December 2020. Difference-in-differences compares June and August.

Treatment Assignment Spending/Outflows

Experiment 3: June 2021 Withdrawal vs. Retain states



(a) UI Inflows



(b) P2P Inflows

Notes: Sample includes those unemployed and insured on April 30. Difference-in-difference compares April to August. Inverse probability weighting by quintile of UI start date.

Treatment Assignment Spending/Outflows

IV diff-in-diff measures of crowd-out

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events

Method	OLS			IV		
Policy Change	March Delays	July Expiration	June Withdrawal	March Delays	July Expiration	June Withdrawal
	(1)	(2)	(3)	(4)	(5)	(6)
UI Inflows	0.003	0.004***	-0.01*	-1.4×10^{-5}	0.008	-0.04*
	(0.004)	(0.002)	(0.006)	(0.005)	(0.006)	(0.02)
Standard-Errors	User		State	User		State
Lower bound × $100 in UI	-0.47284	0.09223	-2.3191	-1.0953	-0.40023	-8.6962
Observations	34,508	31,746	28,546	34,508	31,746	28,546
R^2	0.73776	0.75915	0.71917	0.73775	0.75912	0.71886
F-test (1st stage), UI Inflows				27,825.4	7,683.9	5,083.0
User and Month fixed effects	✓	✓	✓	✓	✓	✓

Instrumental variable difference-in-difference estimates of crowd-out of P2P Inflows by unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conditional on P2P Use | Logged Results | Extensive Margin | Poisson Regression | Single Mothers | Per Capita Income | Economic Connectedness

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Sufficient statistics welfare framework (Chetty and Saez, 2010)

- Workers have ex ante unknown ability n distributed $F(n)$ and utility $u(c) - h(z/n)$
  - Employed: earn z and pay tax τ and private contract τ_p
  - Unemployed: receive public and private benefits b and b_p
  - Crowd-out of b_p by b denoted $r = -db_p/db$
- Work if and only if $n > n^* \rightarrow e = 1 - F(n^*)$ work, $\varepsilon_{1-e,b}$ is unemployment elasticity
- Government chooses b to maximize welfare, yielding the welfare money metric

$$G(b) = \Bigg[\qquad \qquad \qquad \Bigg]$$

Derivation With networks

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- Work if and only if $n > n^* \to e = 1 - F(n^*)$ work, $\varepsilon_{1-e,b}$ is unemployment elasticity

- Government chooses b to maximize welfare, yielding the welfare money metric

$$G(b) = (1-r)\left[\underbrace{\frac{u'(c_u) - u'(c_e)}{u'(c_e)}}_{\text{Marginal utility gap}} - \underbrace{\frac{\varepsilon_{1-e,b}}{e}}_{\text{Moral hazard}} \times \underbrace{\frac{1 + b_p/b}{1-r}}_{\text{Crowd-out}}\right]$$

Derivation With networks

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  - Unemployed: receive public and private benefits b and b_p
  - Crowd-out of b_p by b denoted $r = -db_p/db$
- Work if and only if $n > n^* \to e = 1 - F(n^*)$ work, $\varepsilon_{1-e,b}$ is unemployment elasticity
- Government chooses b to maximize welfare, yielding the welfare money metric

$$G(b) = (1-r)\left[\underbrace{\frac{u'(c_u) - u'(c_e)}{u'(c_e)}}_{\text{Marginal utility gap}} - \underbrace{\frac{\varepsilon_{1-e,b}}{e}}_{\text{Moral hazard}} \times \underbrace{\frac{1 + b_p/b}{1-r}}_{\text{Crowd-out}}\right]$$

$$= (1-r)\left[\left(\frac{c_e}{c_u}\right)^{\gamma} - 1 - \frac{\varepsilon_{1-e,b}}{e} \times \frac{1 + b_p/b}{1-r}\right] \quad \text{under CRRA}$$

Derivation   With networks

Small crowd-out estimates have negligible welfare consequences

- Crowd-out estimates: $r = -db_p/db \in [-0.008, 0.04]$
- "Size of informal insurance" is ratio of average monthly "excess P2P" and UI inflows
  - $b_p/b = 0.06$ before pandemic or 0.01 during pandemic
- Pandemic welfare reaches zero if $b_p/b = 1.12$ with $r = 0.04$

Context	ε	e	r	b_p/b	Standard	With crowd-out
Pandemic	.07	.85	-.008	.01	.10	.10
Pandemic	.07	.85	.04	.01	.10	.09
Pre-pandemic	.5	.95	-.008	.06	-.34	-.36
Pre-Pandemic	.5	.95	.04	.06	-.34	-.37

Table: Money metric welfare effects of UI with and without crowd-out. Elasticities from Ganong et al. (2022). Employment share from Ansell and Mullins (2021) and CPS. Consumption change (8%) taken from Ganong and Noel (2019) and CRRA $\gamma = 2$ from Chetty (2006).

Excess P2P calculation | Excess P2P share | Raw P2P share | SIPP informal share

Conclusion

- People receive a modest amount of informal support via P2P after a job loss
- Informal support targets based on perceived need, somewhat limited by network income
- Small crowd-out implies UI can raise welfare by pooling risk across networks without reducing targeted within-network support
- Empirical justification for policymakers to “ignore” crowd-out when setting benefit levels

Thank you!

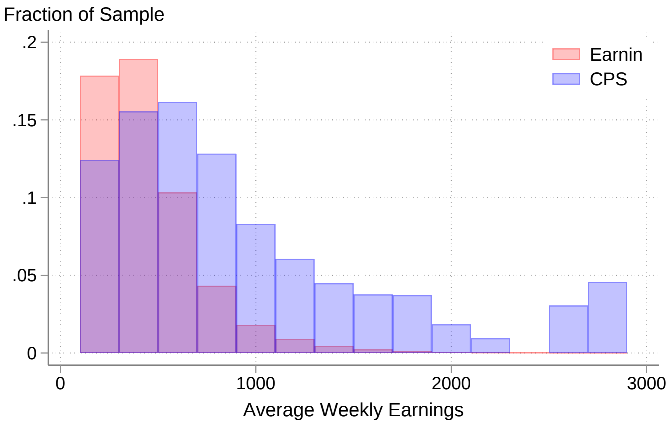
- Questions?
- Comments?
- Compliments?

Synthetic Panel Coverage

- Users not uniquely identified, but flagged by 16 week-varying and 16 fixed "tags"
  - Week-varying: employer zip code, employer NAICS code
  - Fixed: Jan 2020 primary job earnings and first/last transaction dates
- Use three specific fixed tags to assign "proxy" IDs:
  - Date and time signed up for Earnin
  - Gender as predicted by user's first name
  - Confidence in that gender prediction
- Sum to proxy ID-month level and assume each cell is a single person

Back

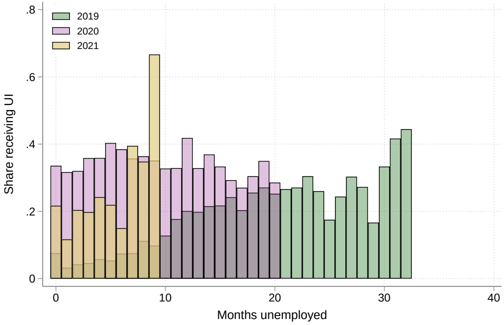
CPS vs. Earnin



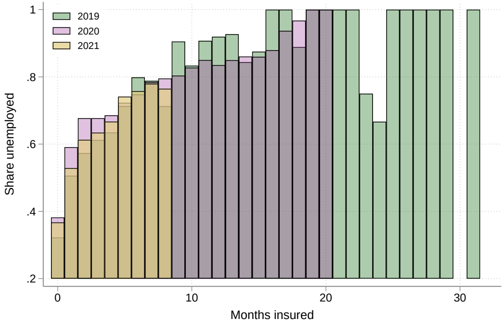
Notes: Comparing average weekly earnings in CPS to Earnin.

Back

Take-up rate low Back



(a) By Unemployment Spell Length



(b) By UI Spell Length

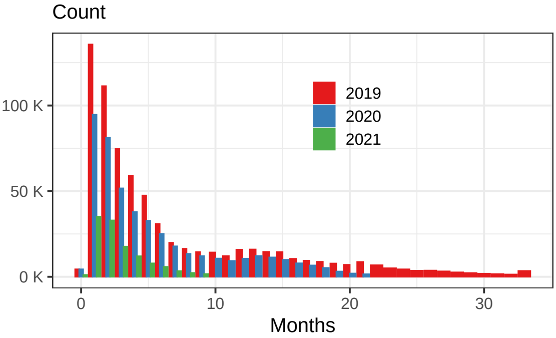
Notes: Figure (a) shows share of users receiving UI within two months of the end of their first unemployment spell by year of job loss and length of spell. Figure (b) shows the share of users that were unemployed within two months of their first UI spell by year and spell length. UI take-up rate was 77 percent from 1989 to 2012 Auray et al. (2019).

Defining earnings and UI

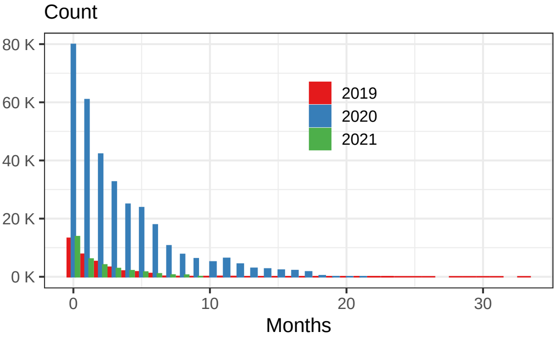
- Earnin provides a series of "verified" earnings transaction amounts for active users
- Match series on transaction amounts and backfill other transactions with matched memos
- Further flag memos considered earnings 90% of the time acros users
- Flag any memos mentioning "Payroll" or "Salary"
- Transactions in one of the "Payroll" groups that occur at least twice, every two weeks, and with a median weekly total between \$500 and \$5,000

Back

Length of unemployment and UI spells



(a) Unemployment



(b) Insured

Notes: Lengths of unemployment and insurance spells.

Back

Private insurance with fixed cost

- There is some private insurance b_p that comes at a hassle cost k
- There is some public insurance b without a fixed cost
- Workers maximize by choosing effort e less some effort cost $C(e)$

$$\max_e eu(z - \tau - \tau^P) + u(b + b_p) - C(e) - k \Rightarrow e(b, k)$$
$$\max_e eu(z - \tau) + u(b) - C(e) \Rightarrow e^*(b)$$

- A worker chooses private insurance if expected utility is higher after hassle cost k
- Threshold b_p^* and db_p^*/db increase in k, but inframarginal crowd-out is the same
- The risk averse are more likely to take b_p at all levels of k

Back

Model of digital payments & income pooling by Jack and Suri (2014)

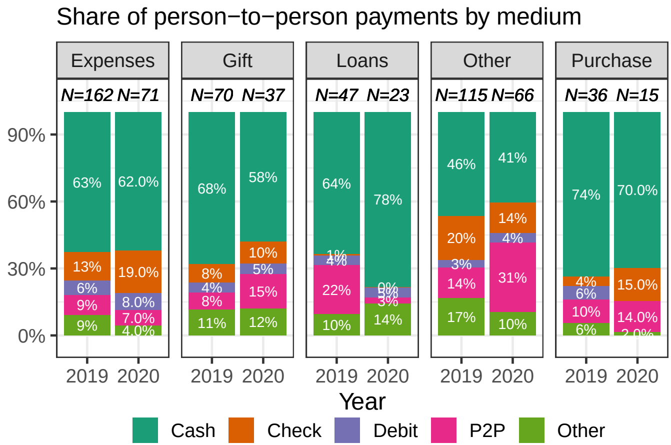
- Consider an economy of three people and S states with endowments x_i s.t. $\sum_i x_i = 1$
- With transfers, Pareto optimization implies welfare $W = 3u\left(\frac{1}{3}\right)$
- A fixed cost k per transfer implies three ex-post welfare outcomes:

$$\underbrace{W(k) = 3u\left(\frac{1-2k}{3}\right)}_{\text{2 transfers}} \quad \underbrace{W(k, x_1) = u(x_1) + 2u\left(\frac{1-x_1-k}{2}\right)}_{\text{1 transfer}} \quad \underbrace{W(x) = \sum_{i=1}^{3} u(x_i)}_{\text{Autarky}}$$

1. As $k \downarrow$, shocks better smoothed $\Rightarrow$ Cash payments should shift to P2P
2. More (smaller) transfers occur $\Rightarrow$ Informal insurance $\uparrow$ with P2P
3. Middle income network members $\uparrow$ $\Rightarrow$ Public insurance crowds out transfers

Back

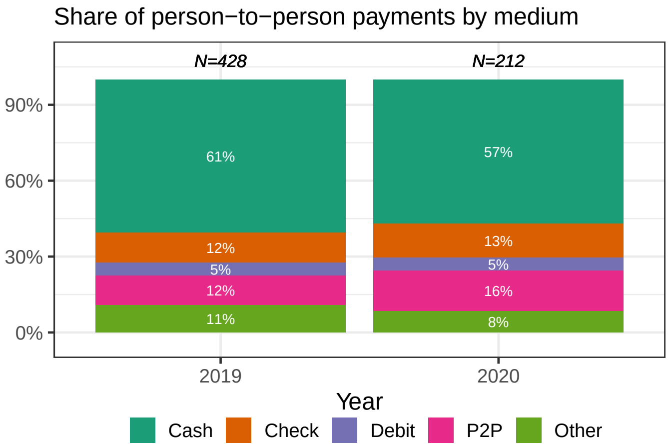
Payment instrument shares by P2P



Notes: Shares by platform of different types of person-to-person payments. Raw data from FRB Atlanta Diary of Consumer Payment Choice.

Back

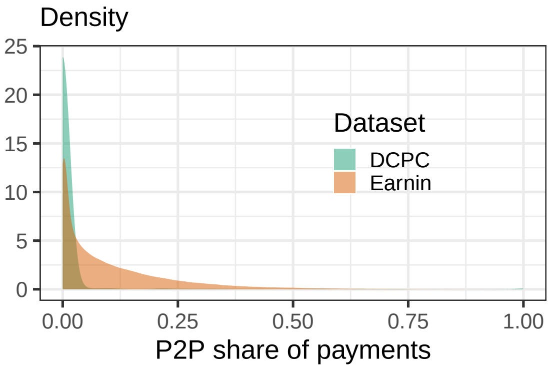
Payment instrument shares over time



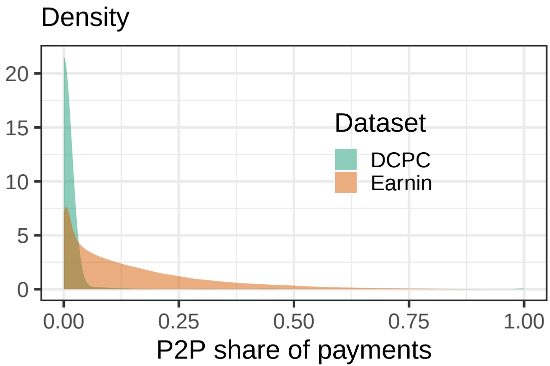
Notes: Shares of person-to-person payments by platform over years. Raw data from FRB Atlanta Diary of Consumer Payment Choice.

Back

P2P flows in Earnin vs. Diary of Consumer Payment Choice



(a) 2019

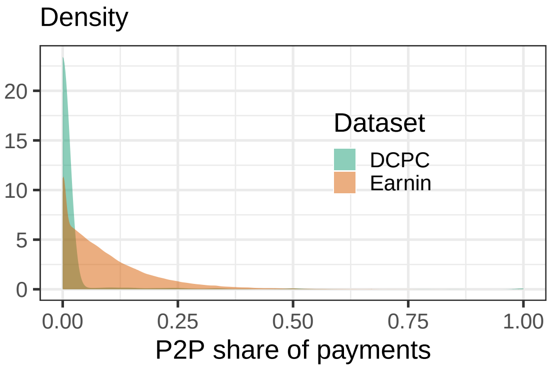


(b) 2020

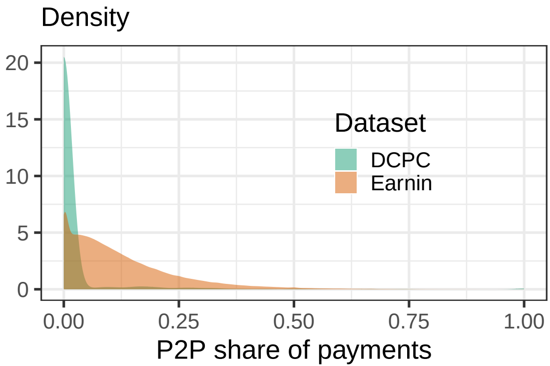
Notes: User share of cumulative non-cash dollar flows linked to P2P platforms in the months of October 2019 (a) and 2020 (b) the Diary of Consumer Payment Choice (DCPC) vs. Earnin database.

Back

P2P use in Earnin vs. Diary of Consumer Payment Choice



(a) 2019

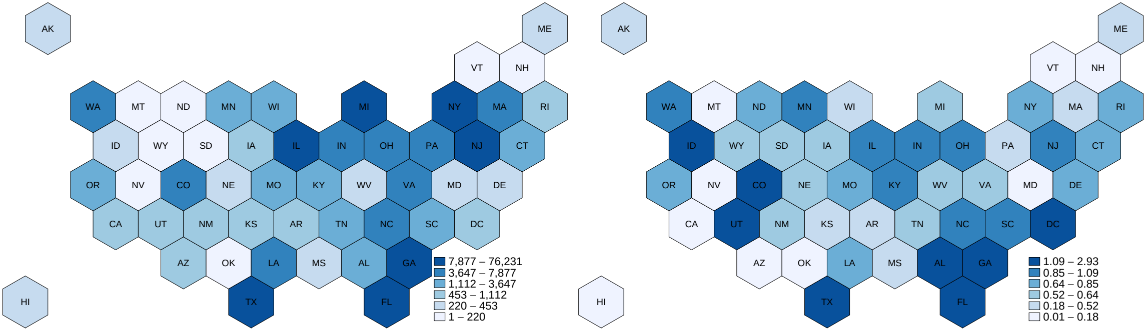


(b) 2020

Notes: User share of non-cash transactions linked to P2P platforms in the months of October 2019 (a) and 2020 (b) the Diary of Consumer Payment Choice (DCPC) vs. Earnin database.

Back

Earnin UI coverage: Lower where states do not direct deposit UI

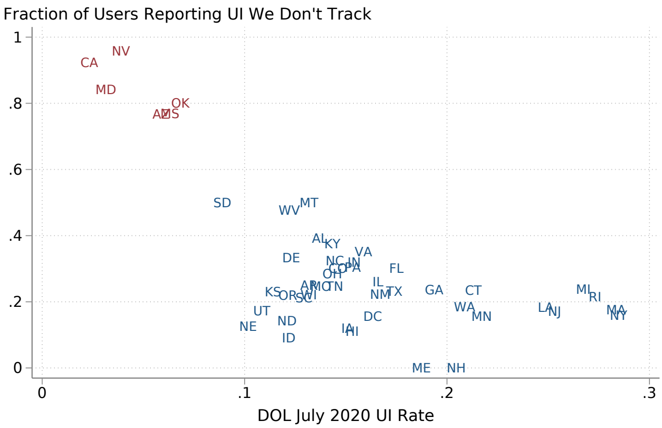


(a) Number of UI Recipients on Earnin (b) Fraction of All UI Recipients on Earnin (%)

Notes: Panel (a) gives the total number of Earnin users who received unemployment benefits through direct deposit during the month of July 2020 by state. Panel (b) gives this total as a percentage of total estimated UI recipients by state as estimated by Chetty et al. (2020)

Categorize Txns Data

Unemployment insurance state misses



July 2020 DOL UI rate vs. fraction of false negatives based on survey – drop states in red.

Transactions Data Analysis Sample

Unemployment Coverage Cross-tabs in Sample

Table: Overall sample selection

	No UI	Had UI	Total
Has job loss	929,193	344,268	1,273,461
	(72.97)	(27.03)	(100.00)
Continuously employed	445,949	58,887	504,836
	(88.34)	(11.66)	(100.00)
Total	1,375,142	403,155	1,778,297
	(77.33)	(22.67)	(100.00)

Two-way tab of users that are unemployed or insured from January 2019 through October 2021.

Back

Gender by Family composition (analysis sample)

Table: Overall sample selection

	Male	Female	Total
Single	28,570	23,809	52,379
	(54.54)	(45.46)	(100.00)
Married, no kids	1,798	1,885	3,683
	(48.82)	(51.18)	(100.00)
Single Parent	5,164	14,974	20,138
	(25.64)	(74.36)	(100.00)
Married, kids	4,203	4,105	8,308
	(50.59)	(49.41)	(100.00)
Total	39,735	44,773	84,508
	(47.02)	(52.98)	(100.00)

Two-way tab of gender and family composition of users in analysis sample.

Back

Gender by Family composition

Table: Overall sample selection

	Male	Female	Total
Single	259,109	208,490	467,599
	(55.41)	(44.59)	(100.00)
Married, no kids	19,400	20,842	40,242
	(48.21)	(51.79)	(100.00)
Single Parent	51,552	136,742	188,294
	(27.38)	(72.62)	(100.00)
Married, kids	47,692	44,103	91,795
	(51.95)	(48.05)	(100.00)
Total	377,753	410,177	787,930
	(47.94)	(52.06)	(100.00)

Two-way tab of gender and family composition.

Back

Analysis sample unemployment by UI

Table: Analysis sample UI receipt

	No UI after first job loss	UI after first job loss	Total
Job loss after 9/2020	4,174	71	4,245
	(98.33)	(1.67)	(100.00)
Job loss 7/2019 to 9/2020	77,080	53,422	130,502
	(59.06)	(40.94)	(100.00)
Total	81,254	53,493	134,747
	(60.30)	(39.70)	(100.00)

Two-way tab of users that are unemployed in analysis sample.

Back

UI Coverage Cross-tabs

Table: UI state quality by tracked UI

	No UI	Had UI	Total
Good UI tracking state	708,805	328,135	1,036,940
	(68.36)	(31.64)	(100.00)
Bad UI tracking state	220,388	16,133	236,521
	(93.18)	(6.82)	(100.00)
Total	929,193	344,268	1,273,461
	(72.97)	(27.03)	(100.00)

Cross tab of users with UI after unemployment by good states.

Back

Analysis sample UI coverage cross-tabs

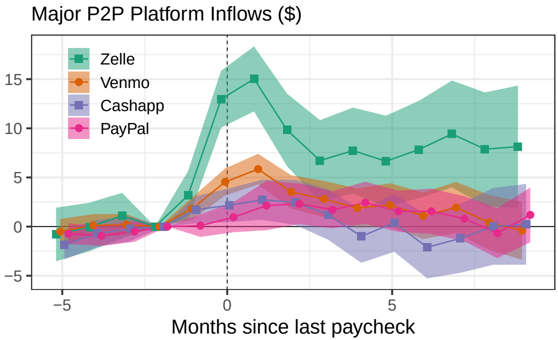
Table: UI state quality by tracked UI analysis sample

	No UI after first job loss	UI after first job loss	Total
Good UI tracking state	56,331	51,850	108,181
	(52.07)	(47.93)	(100.00)
Bad UI tracking state	24,923	1,643	26,566
	(93.82)	(6.18)	(100.00)
Total	81,254	53,493	134,747
	(60.30)	(39.70)	(100.00)

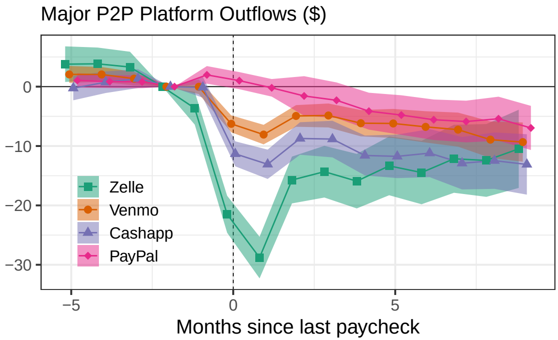
Cross tab of users with UI after unemployment by good states in analysis sample.

Back

Major P2P platforms



(a) Inflows

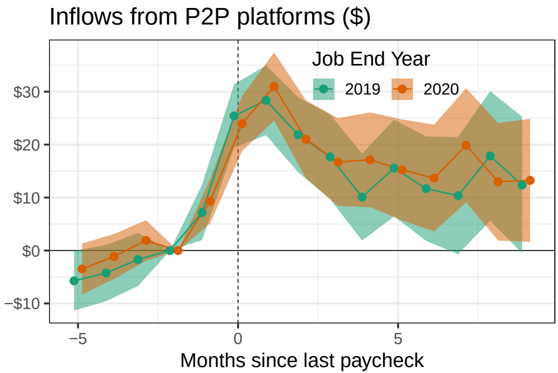


(b) Outflows

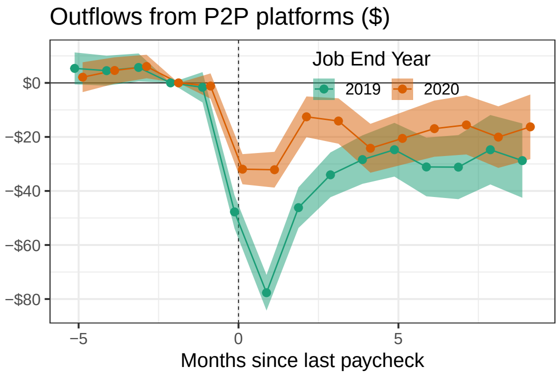
Notes: Inflow and outflow event studies for memos mentioning selected large P2P platforms. "Purchase" memos removed.

Main Event Study

Difference in behavior by year?



(a) Inflows

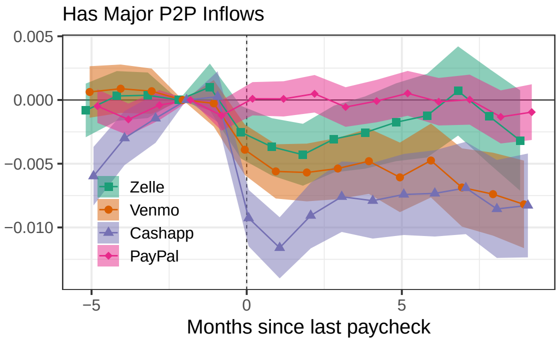


(b) Outfows

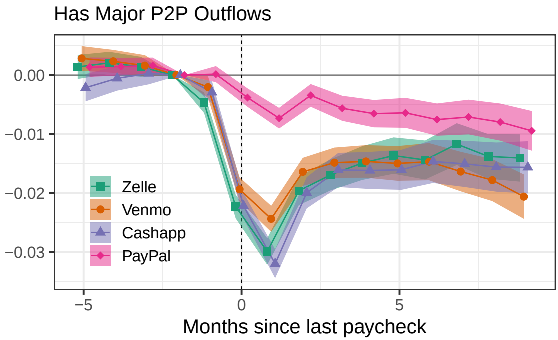
Notes: Event study of inflows and outflows from any P2P platform less purchaes memos. Coefficients on time dummies interacted with year of unemployment start plotted.

Main Event Study

Used Major P2P platforms



(a) Inflows

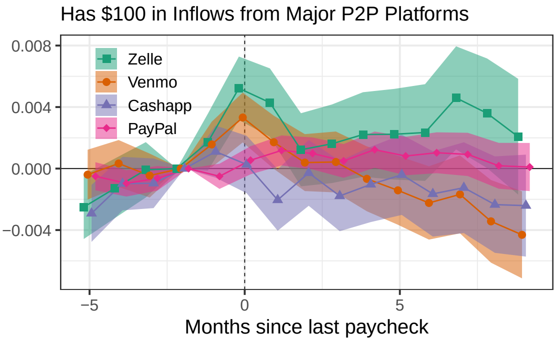


(b) Outflows

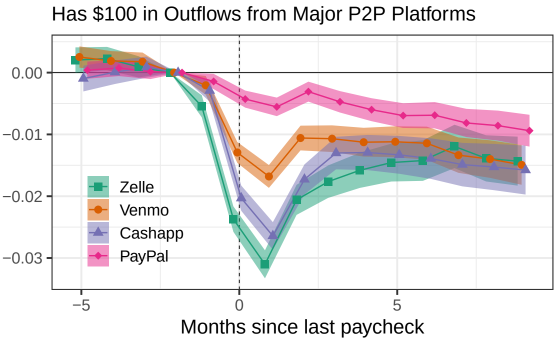
Notes: Event studies for having any monthly inflows and outflows on selected large P2P platforms. "Purchase" memos removed.

Back

At least $100 on Major P2P platforms



(a) Inflows

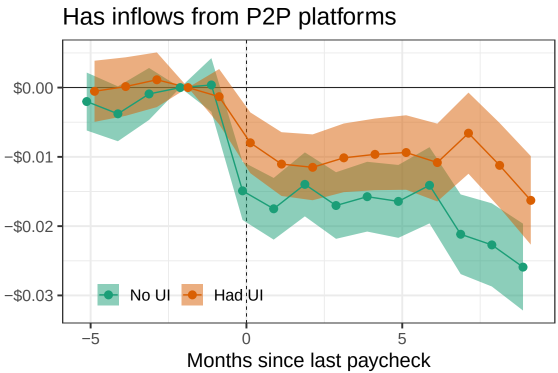


(b) Outflows

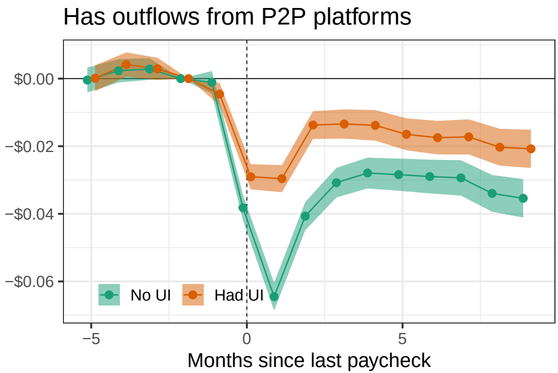
Notes: Event studies for having at least $100 of monthly inflows and outflows on selected large P2P platforms. "Purchase" memos removed.

Back

Used P2P by UI status



(a) Inflows

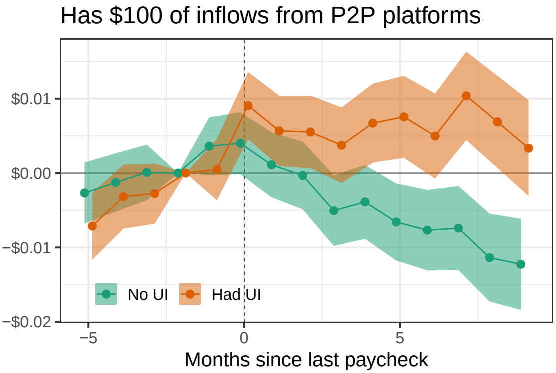


(b) Outflows

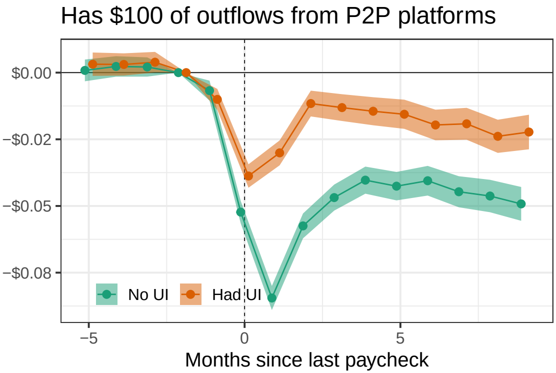
Notes: Event studies for having monthly inflows and outflows interacted with whether user received UI after unemployment or not. "Purchase" memos removed.

Back

At least \$100 of P2P by UI status



(a) Inflows

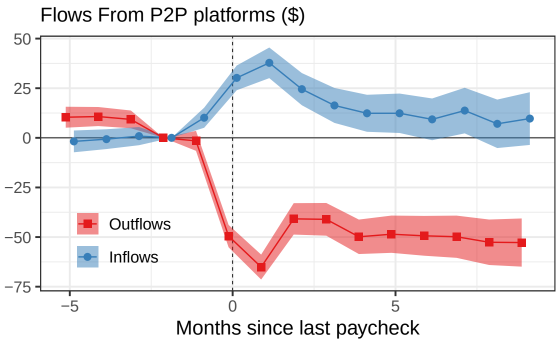


(b) Outflows

Notes: Event studies for having at least \$100 of monthly inflows and outflows interacted with whether user received UI after unemployment or not. "Purchase" memos removed.

Back

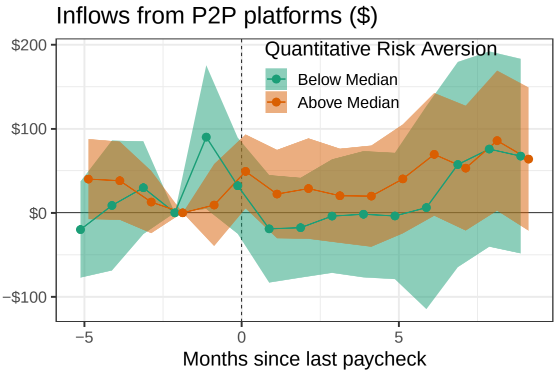
Conditional on prior use



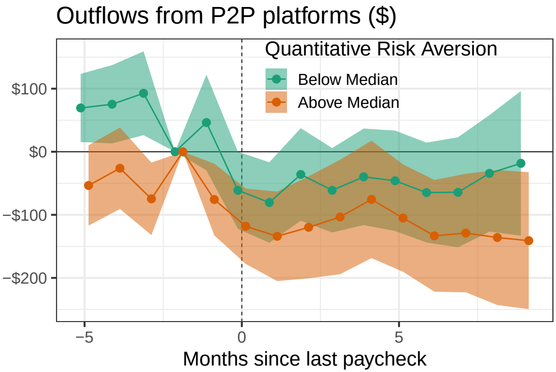
Notes: Event studies of inflows and outflows of any P2P platform around an unemployment event conditional on P2P use at least six months prior.

Main Event Study

The risk averse get transfers early



(a) Inflows



(b) Outflows

Notes: Inflow and outflow event study coefficients interacted with whether above or below median risk aversion. “Purchase” memos removed.

Main Event Study | Quantitative Risk | Qualitative Risk

Survey Design

- Conducted surveys in August 2020 ($N \approx 26K$) and 2021 ($N \approx 12K$)
  - Total income, UI received and spending in prior month and expected in next month
  - Savings in bank account at time of survey
  - Past/current/reservation wage
  - Dates last worked, expect to work again, etc.
  - Part-time/full-time status of work
  - Race, ethnicity, gender, age, marital status, children, education,
  - **Risk preferences:** Telescoping question of preference between 50-50 gamble for $0 or $M vs. sure payment of $240 (Falk et al., 2016)
  - **Discount preferences:** Money in three months preferred to $40 in a week
  - Qualitative risk and discount preferences questions: 1-10 scale
- Sample frame: 500K users with active accounts in March 2020, 50% UI recipients and 50% non-recipients
- Compensated first 2000 with $5 Amazon gift card

Main Event Study | Transactions data

Risk preferences (quantitative)

Please imagine the following situation: You can choose between a sure payment of a particular amount of money, OR a draw, where you would have an equal chance of getting **$450** (U.S. dollars) or getting nothing. We will present to you five different situations.

* 21. What would you prefer: A draw with a 50-percent chance of receiving **$450** and the same 50-percent chance of receiving nothing, OR the amount of **$240** as a sure payment?

- ◯ 50/50 chance
- ◯ Sure payment
- ◯ Prefer not to say

Main Event Study | Transactions data | Risk Aversion Event Study

Risk preferences (qualitative)

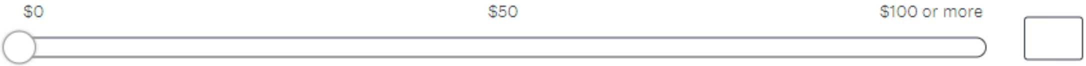
22. Please tell us, in general, how willing or unwilling you are to give up something that is beneficial for you today in order to benefit more in the future, using a scale from 0 to 10, where 0 means you are "completely unwilling to do so" and 10 means you are "very willing to do so." You can also use any number between 0 and 10 to indicate where you fall on the scale.

- ◯ 10 - very willing to give up something that is beneficial for me today in order to benefit more in the future
- ◯ 9
- ◯ 8
- ◯ 7
- ◯ 6
- ◯ 5
- ◯ 4
- ◯ 3
- ◯ 2
- ◯ 1
- ◯ 0 - completely unwilling to give up something that is beneficial for me today in order to benefit more in the future

Main Event Study | Transactions data | Risk Aversion Event Study

Discount preferences (quantitative)

23. Suppose someone was going to pay you $40 one week from now. They offer to pay you a higher amount in three months' time instead. **What amount of money in three months** would make you just as happy as receiving **$40 in one week**?



Main Event Study | Transactions data | Risk Aversion Event Study

Two-Stage Difference-in-differences Gardner (2022)

- Gardner (2022) introduced a two-stage DiD imputation approach to manage staggered timing and heterogeneous treatment effects

- Estimate difference in differences/event study in two stages
  1. Residualize outcomes month and user fixed effects estimates from the untreated/not-yet-treated observations
  2. Regress residualized outcome on the treatment indicator(s)

$$y_{it}(0) = \lambda_i + \lambda_t + \nu_{it}$$

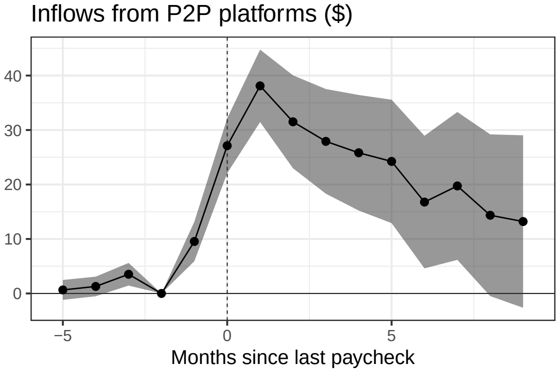
$$\tilde{y}_{it} = y_{it} - \hat{\mu}_t - \hat{\mu}_t$$

$$\tilde{y}_{it} = \sum_{s \in [-4,-2]} \beta_s D_{it}^s + \sum_{s \in [0,9]} \beta_s D_{it}^s + \beta_{-5} \sum_{s \leq -5} D_s^t + \beta_{10} \sum_{s \geq 10} D_{it}^s + \varepsilon_{it}$$

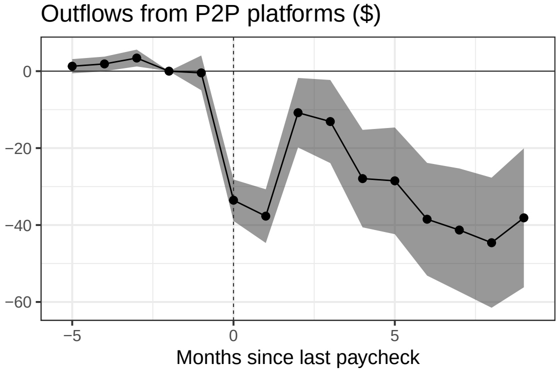
- The continuously employed until September 2021 is a "not yet treated" group

Main Event Study

Gardner Two-Stage Event Study



(a) Inflows

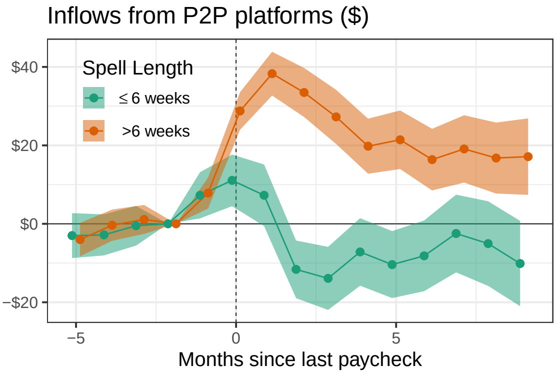


(b) Outflows

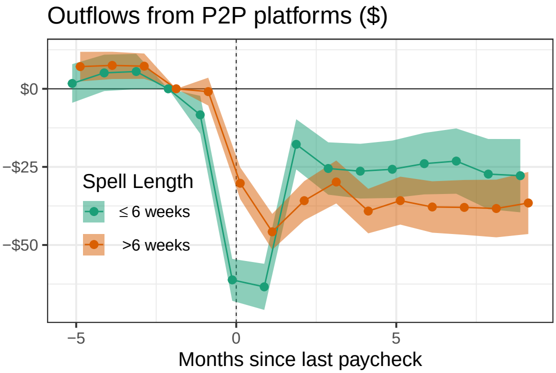
Notes: Gardner Two-Stage DiD corrects for "bad comparisons." Standard errors bootstrapped user-level clusters.

Main Event Study

P2P flows by whether unemployment spell lasted longer than six weeks



(a) Inflows

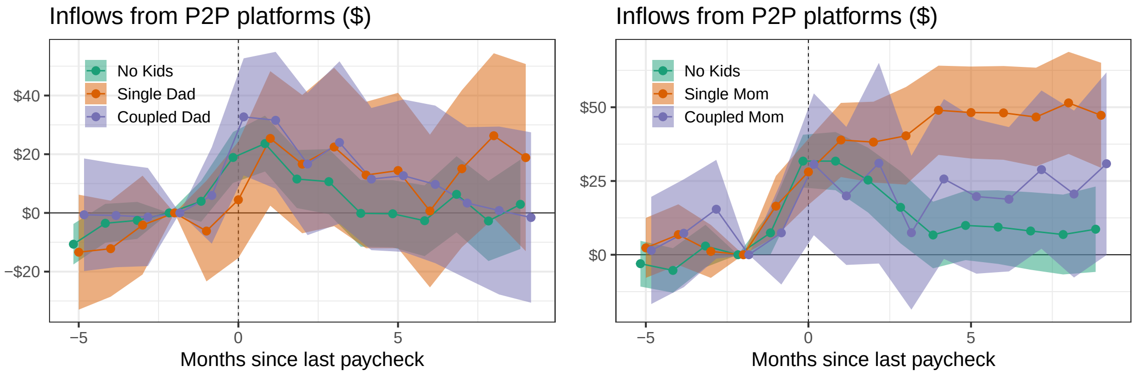


(b) Outflows

Notes: Event studies subset by whether spell is longer than six weeks or not.

Main Event Study   Cumulative

P2P inflows by gender, parentage, relationship

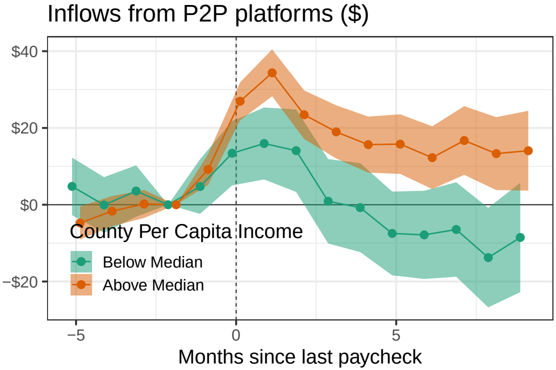


(a) Men (b) Women

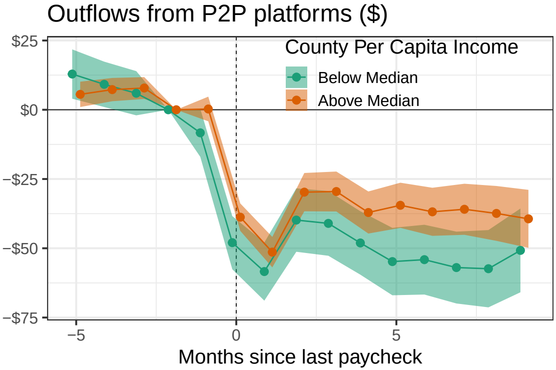
Notes: P2P inflows and outflows by gender and family composition as determined by survey response, observed receipt of CTC, or stimulus payment amount.

Cumulative

P2P flows by per capita income of county



(a) Inflows

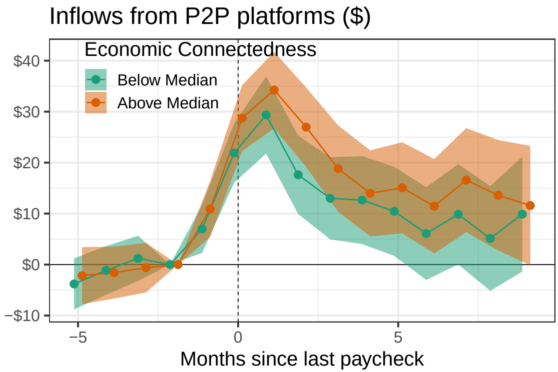


(b) Outflows

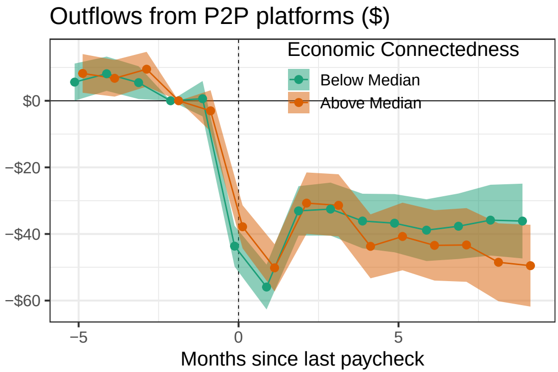
Notes: P2P response to living in an above or below median per capita household income county as measured by the American Community Survey 2019 5-year

Cumulative

P2P inflows by economic connectedness of zip code



(a) Inflows



(b) Outflows

Notes: P2P response to living in an above or below median per capita household income county as measured by economic connectedness in Social Capital Atlas (Chetty et al., 2022).

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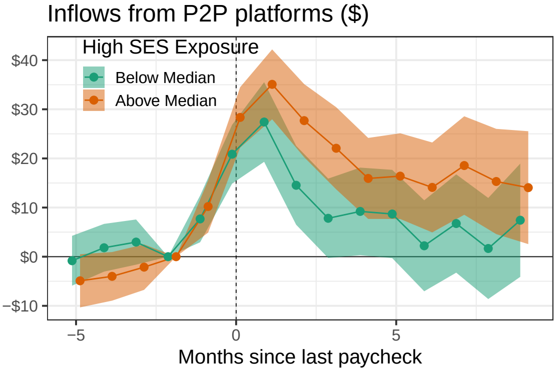
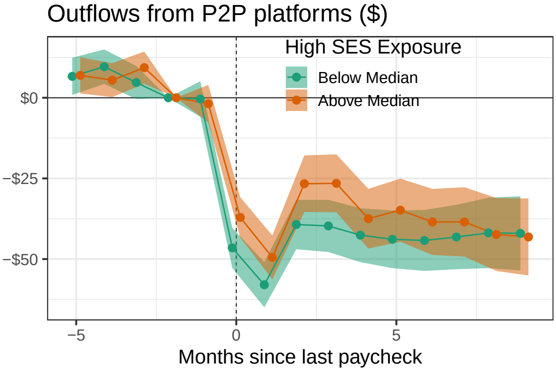
P2P inflows by high-SES exposure of zip code



(a) Inflows

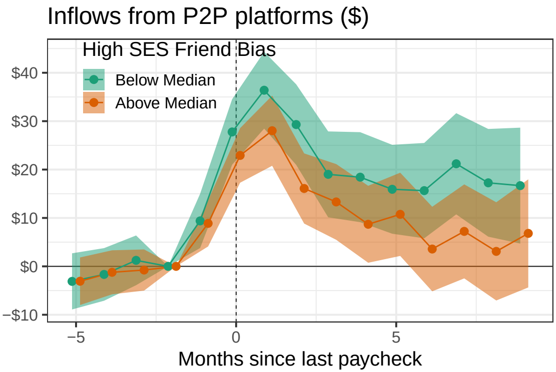


(b) Outflows

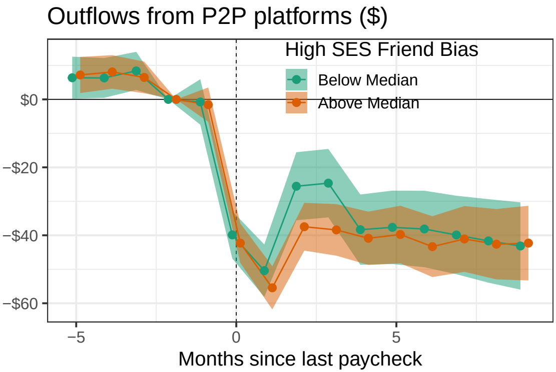
Notes: P2P response to living in an above or below median per capita household income county as measured by high-SES expsoure in Social Capital Atlas (Chetty et al., 2022).

Back

P2P inflows by friending bias of zip code



(a) Inflows



(b) Outflows

Notes: P2P response to living in an above or below median per capita household income county as measured by high-SES friending bias in Social Capital Atlas (Chetty et al., 2022).

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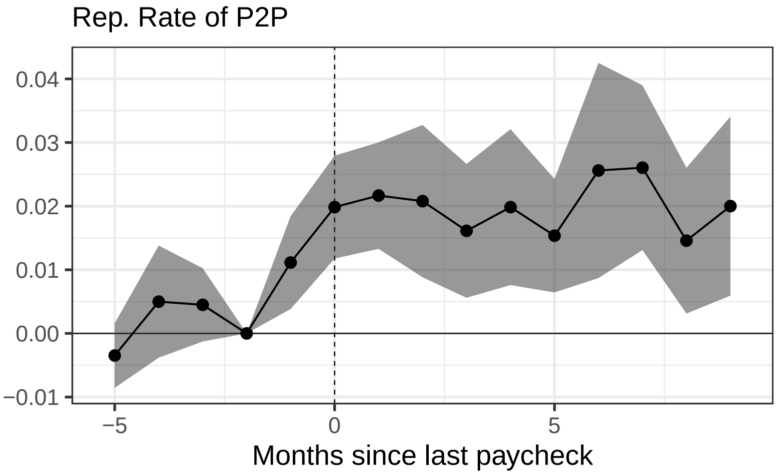
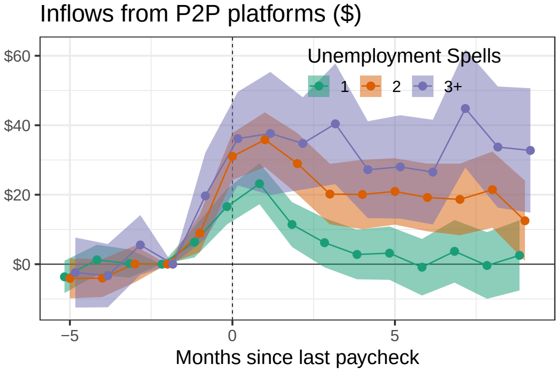
P2P replacement rate

Main Event Study Income Loss

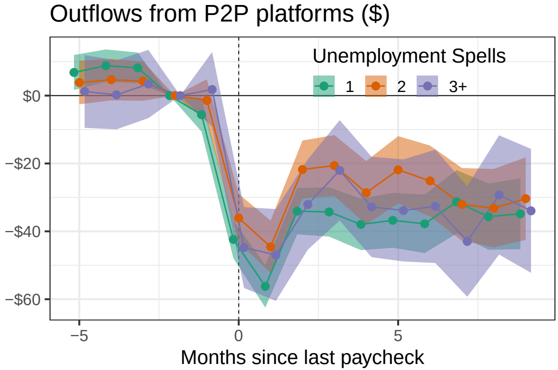


Notes: Event studies of inflows of P2P normalized by pre-job loss earnings.

How many spells of unemployment?



(a) Inflow

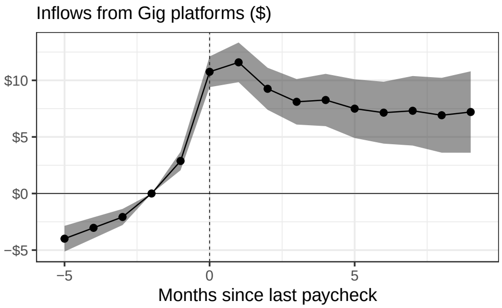


(b) Outflow

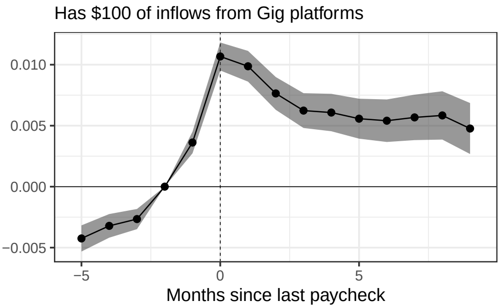
Notes: Event study of P2P inflows and outflows time dummies interacted with number of unemployment spells.

Main Event Study

Gig employment behavior



(a) Gig Earnings

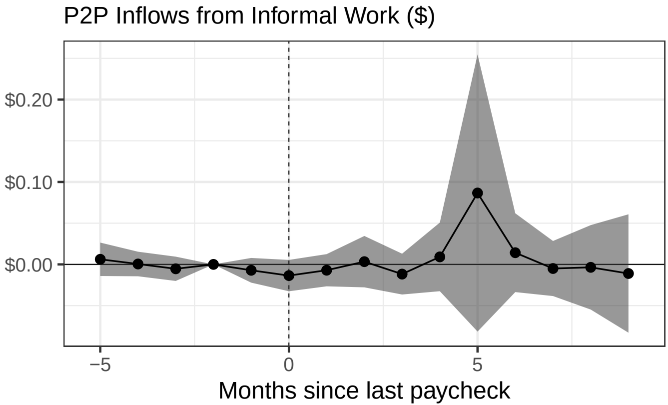


(b) > $100 Gig Earnings

Notes: Within-person event study of gig work earnings and the probability that gig work earnings exceed $100 around month of job loss. Standard error's clustered at the user-level.

Main Event Study | Extensive Margin

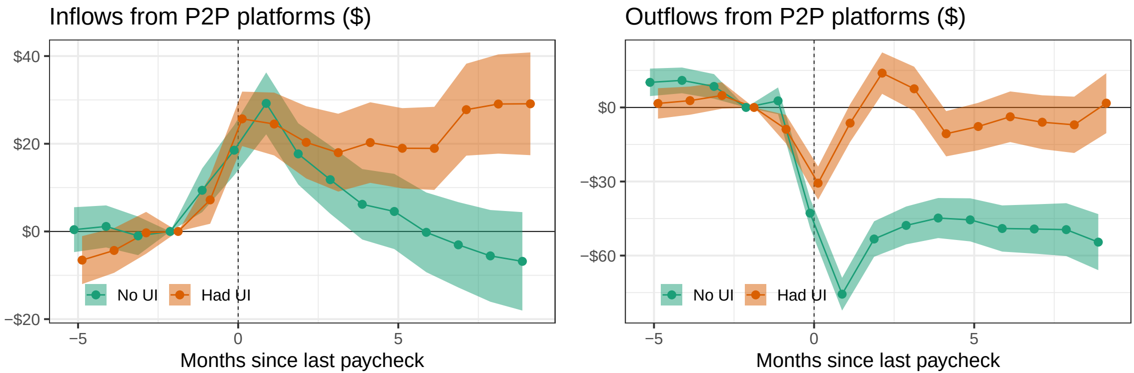
Informal P2P Earnings



Notes: Within-person event study of informal earnings on P2P platforms.

Main Event Study

Conditional on getting UI

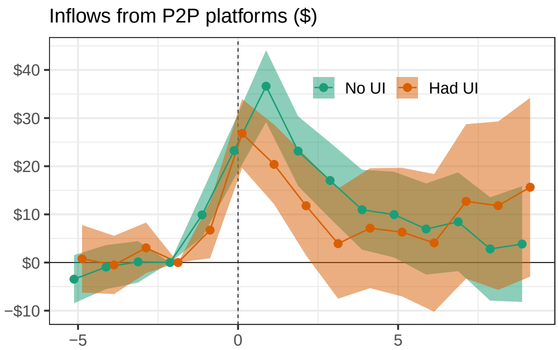


(a) Inflows (b) Outflows

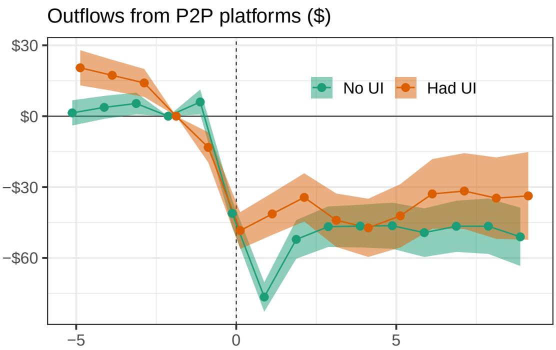
Notes: Event studies inflows and outflows from P2P platform around unemployment. Coefficients on relative time dummies interacted with UI receipt indicators plotted. Purchase memos removed.

Time to UI Subsample split Replacement rate

Within UI receipt groups



(a) Inflows

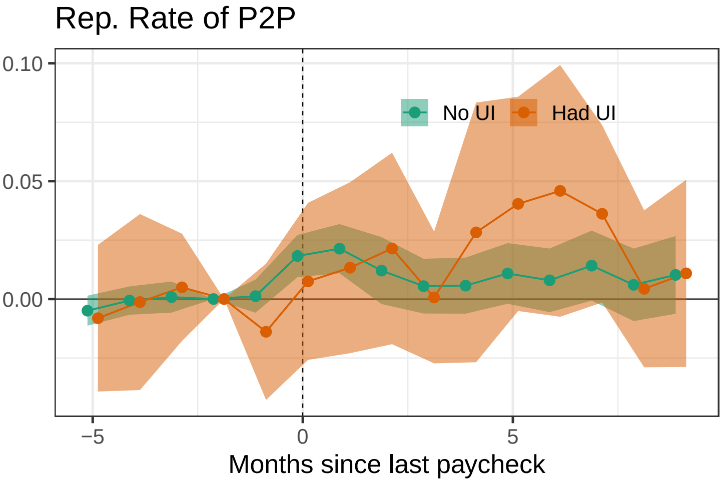


(b) Outflows

Notes: Event studies subset by whether the user had UI after unemployment or not.

Time to UI | Main Event Study

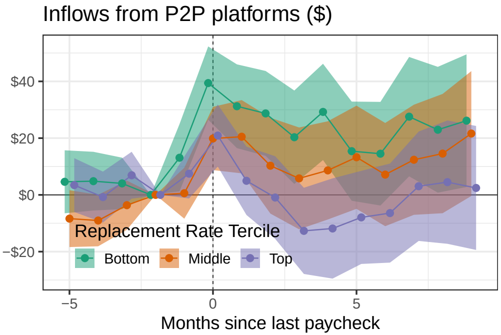
P2P replacement rate by UI receipt



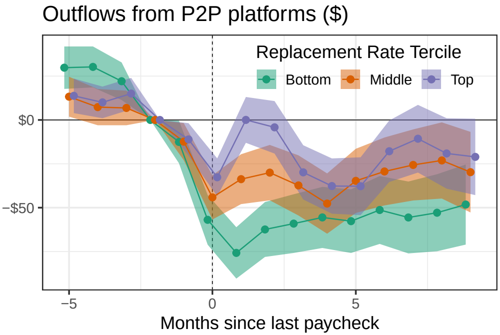
Notes: Event studies of inflows of P2P normalized by pre-job loss earnings by UI receipt.

Time to UI
Conditional on UI

UI replacement rate tercile



(a) P2P Inflows

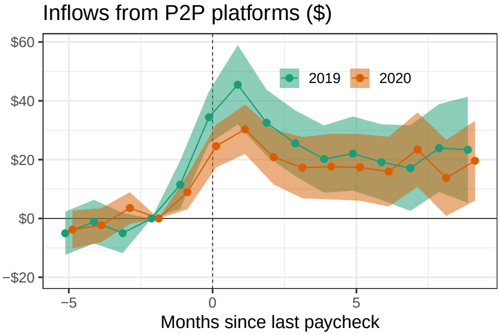


(b) P2P Outflows

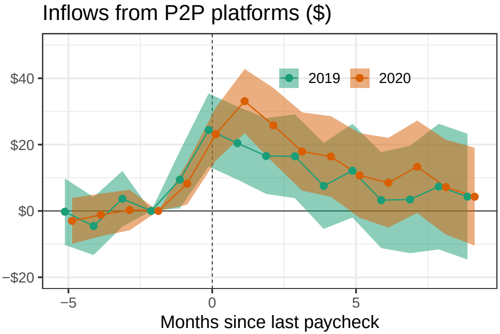
Notes: Within-person event study coefficients are interacted with tercile of user pre-job loss earnings replacement rate. Sample restricted to users with a single job loss and and excluding users in states that do not have easily identifiable UI deposit memos. Standard error's clustered at the user-level.

Time to UI | Conditional on UI

State-level replacement rate from Ganong et al. (2020)



(a) Below Median

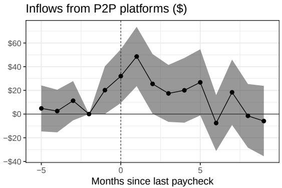


(b) Above Median

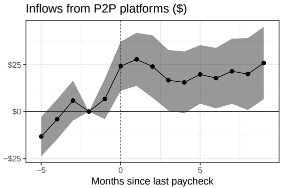
Notes: Figures shows event study of P2P inflows with coefficients interacted with: (1) whether above or below the median replacement rate for a state and (2) the year of job loss. Median pre-job loss earnings replacement by Ganong et al. (2020). Standard errors clustered at user-level.

Time to UI Conditional on UI

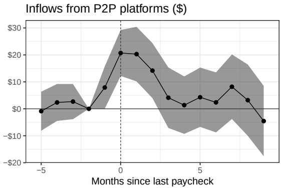
Selected NAICS groups



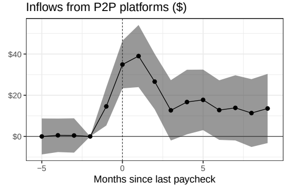
(a) Educational Services



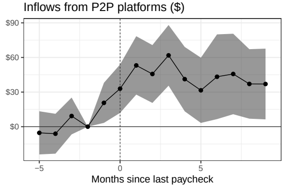
(b) Healthcare & Social Services



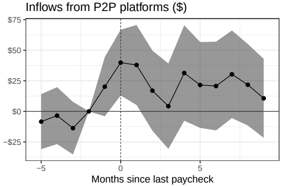
(c) Retail Trade



(d) Accommodation and Food Services



(e) Transportation & Warehousing

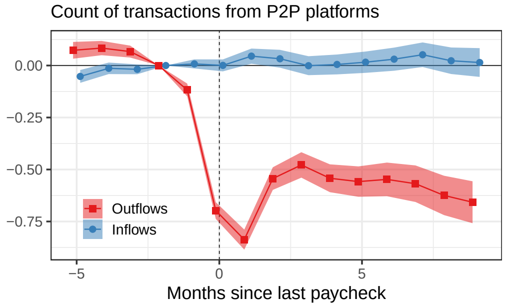


(f) Arts, Entertainment, Recreation

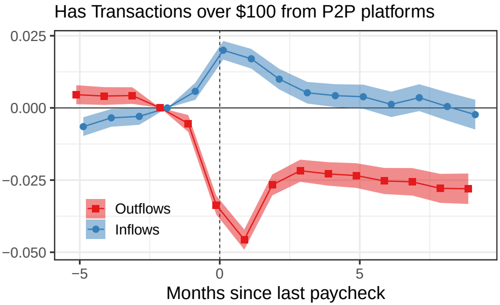
Notes: P2P inflow event study coefficients interacted with NAICS category of former job.

Main Event Study

Transaction counts and size



(a) Count of P2P transactions



(b) $\mathbb{P}(\text{P2P transaction} > 100)$

Notes: Event study of whether the user had inflows, outflows, or either transactions from a P2P platform. The sample is restricted to users with a single unemployment spell. coefficients Standard error's clustered at the user-level.

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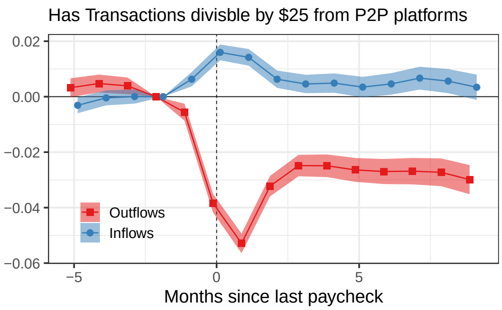
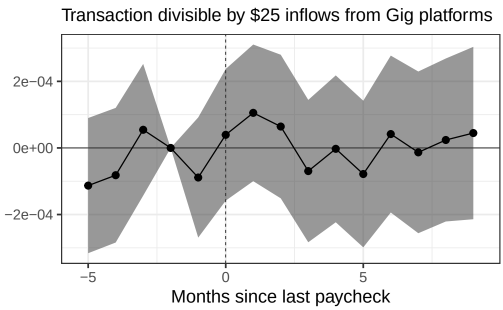
Transactions divisible by $25



(a) $\mathbb{P}$(P2P transaction divible by 25)



(b) $\mathbb{P}$(Gig earning transaction divible by 25)

Notes: Event studies of the probability of a transaction divisible by $25 from P2P inflows, outflows, or gig earnings.

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Defining "active" users of P2P

- To quantify tercile of P2P activity I do the following:
  - Calculate monthly share of cumulative flows linked to P2P platforms
  - Take the median of these monthly shares for months 3+ months prior to job loss
  - Calculate the tercile of these median monthly shares
- Interact event study coefficients with each tercile

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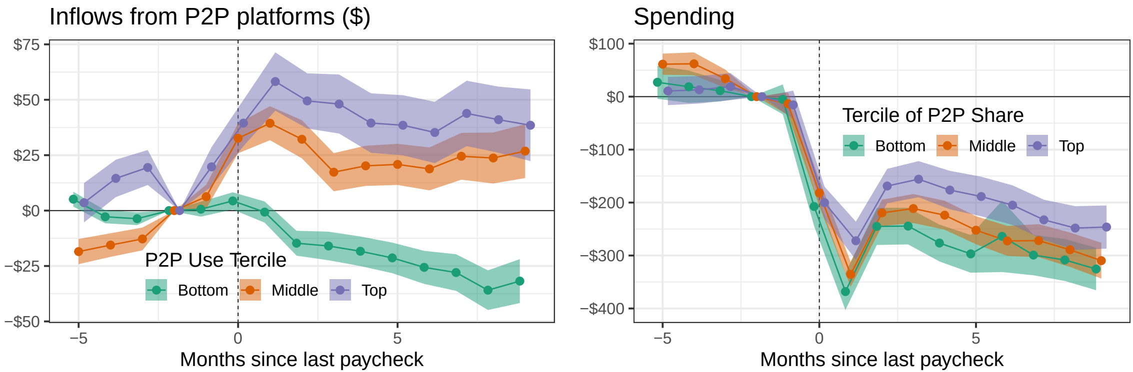
“Active” users receive more P2P and smooth consumption more



(a) P2P Inflows (b) Spending

Notes: Coefficients are interacted with indicators for the tercile of median monthly share of flows linked to P2P more than three months before job loss.

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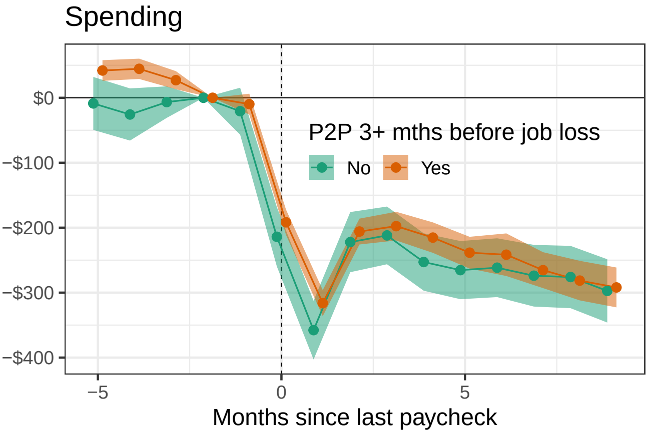
Using P2P at least 3+ months prior



Notes: Coefficients are interacted with indicator for using P2P more than three months before job loss.

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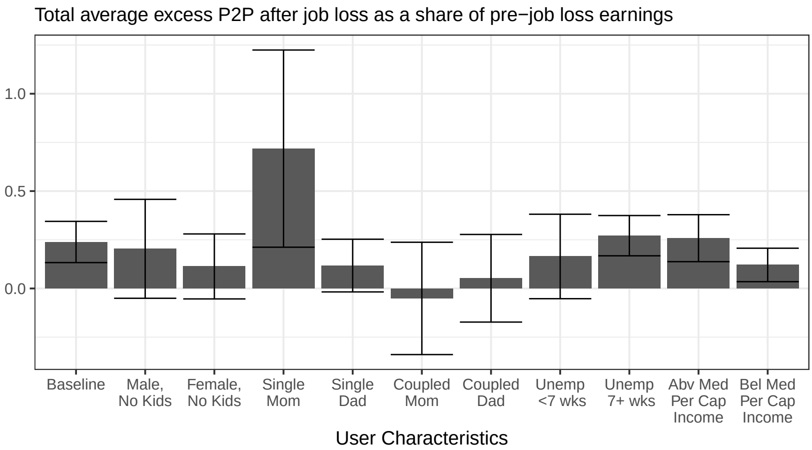
Heterogeneity in cumulative support as a share of earnings



Notes: Total P2P rep. rate after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

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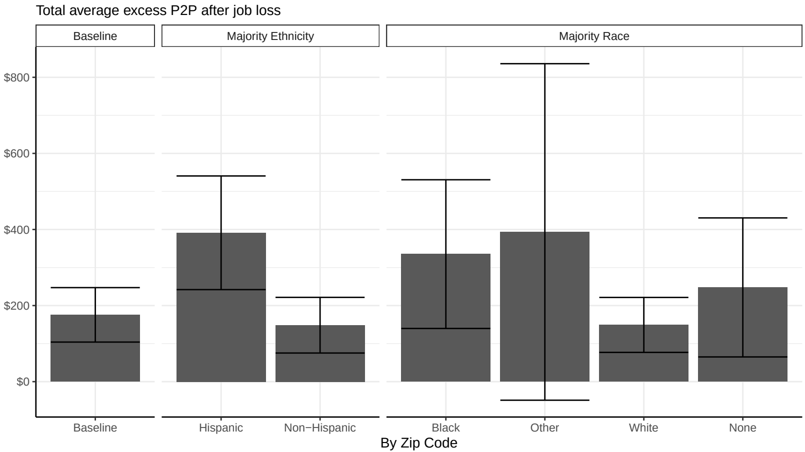
Users in Majority-Minority zip codes get more support



Notes: Total excess P2P after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Race & ethnicity shares by zip code.

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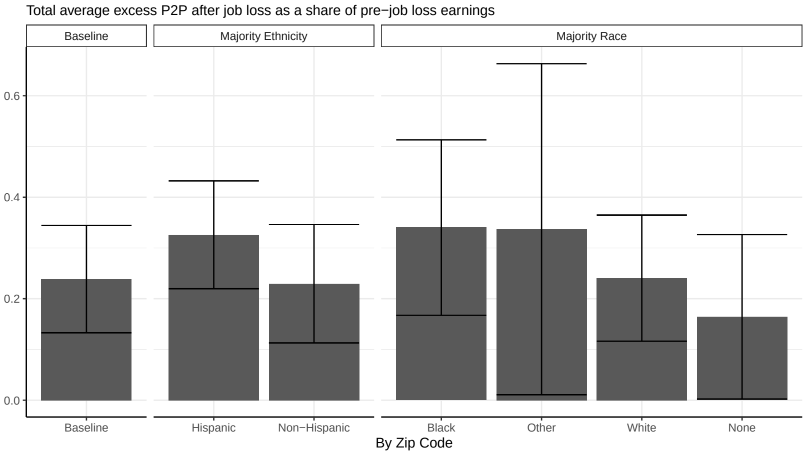
Users in Majority-Minority zip codes get more support



Notes: Total P2P rep. rate after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Race & ethnicity shares by zip code.

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Economic Connectedness Decomposition

Formally, economic connectedness of individual i to above-median-SES individuals H:

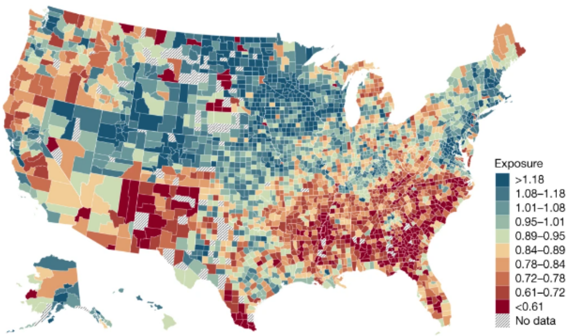
$$\mathrm{IEC}_{H,i} = \frac{f_{H,i}}{w_H} = \sum_{g \in G} \left[\varphi_{i,g} \times \frac{f_{H,i,g}}{w_H} \right] = \sum_{g \in G} \left[\varphi_{i,g} \times \frac{w_{H,g}}{w_H} \times \frac{f_{H,i,g}}{w_{H,g}} \right]$$
$$= \sum_{g \in G} \left[\varphi_{i,g} \times \text{Exposure}_{H,g} \times \left(1 - \text{Friending bias}_{H,i,g} \right) \right]$$

where

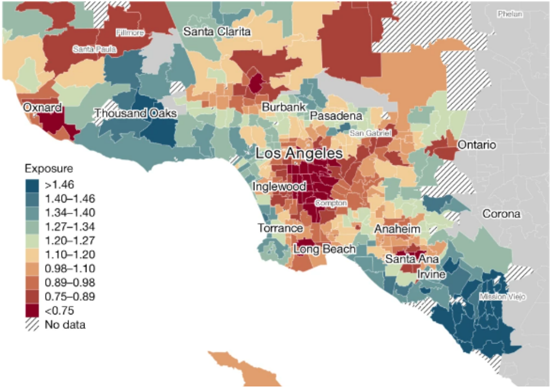
$$\text{Exposure}_{H,g} \equiv \frac{w_{H,g}}{w_H}$$
$$\text{Friending bias}_{H,i,g} \equiv 1 - \frac{f_{H,i,g}}{w_{H,g}}$$

where w_H represents high-SES population share, $f_{H,i}$ is the high-SES friend share, and $\varphi_{i,g}$ is friend share within each zip code g Back

Social Capital Atlas: Exposure by county and selected zip codes



(a) County



(b) Zip codes in LA

Notes: Social Capital Atlas measure of Exposure to above-median SES individuals by (a) county and (b) zip code within Los Angeles County. Sources: Chetty et al. (2022)

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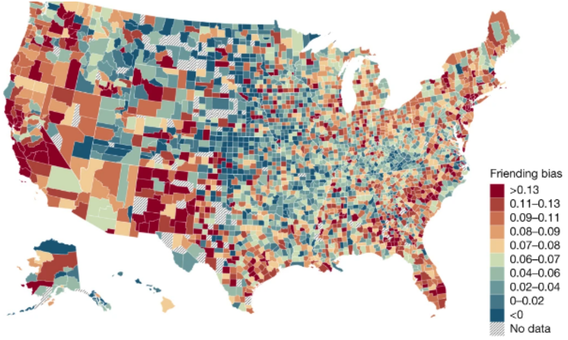
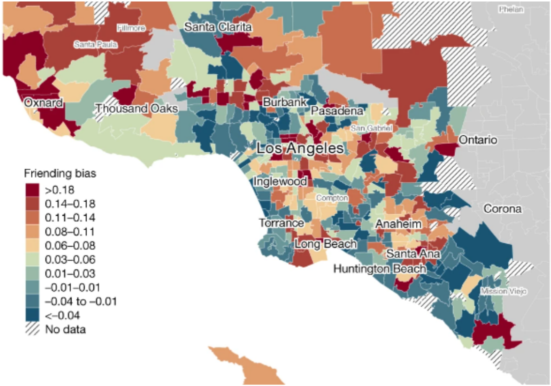
Social Capital Atlas: Friending bias by county and selected zip codes



(a) County



(b) Zip codes in LA

Notes: Social Capital Atlas measure of Friending bias to above-median SES individuals by (a) county and (b) zip code within Los Angeles County. Sources: Chetty et al. (2022)

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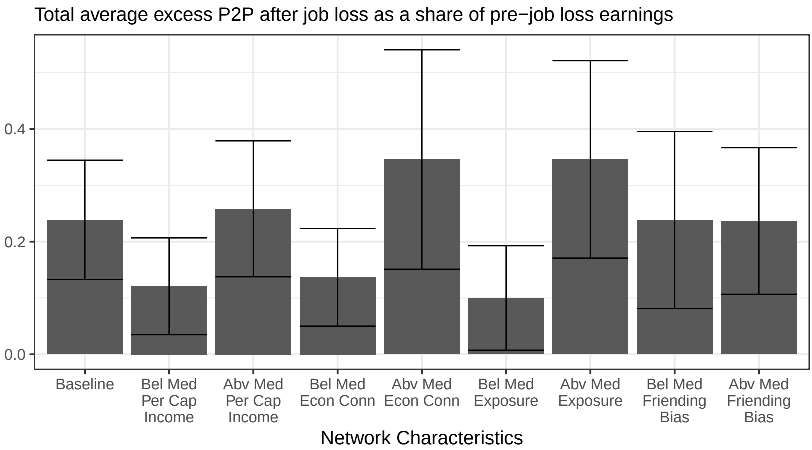
Economic Connectedness replacement rates



Notes: Cumulative excess P2P replacement rate after job loss calculated as the sum of event study coefficients for relative months -1 through 10 interacted with the relevant group shown on the x-axis.

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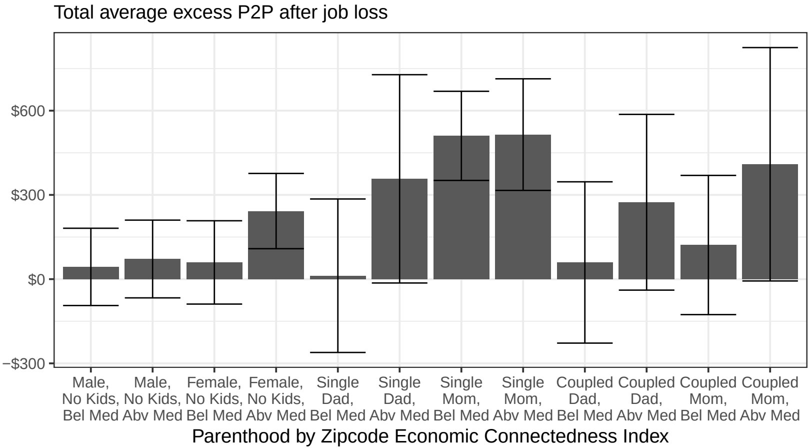
Parenthood by Economic Connectedness



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

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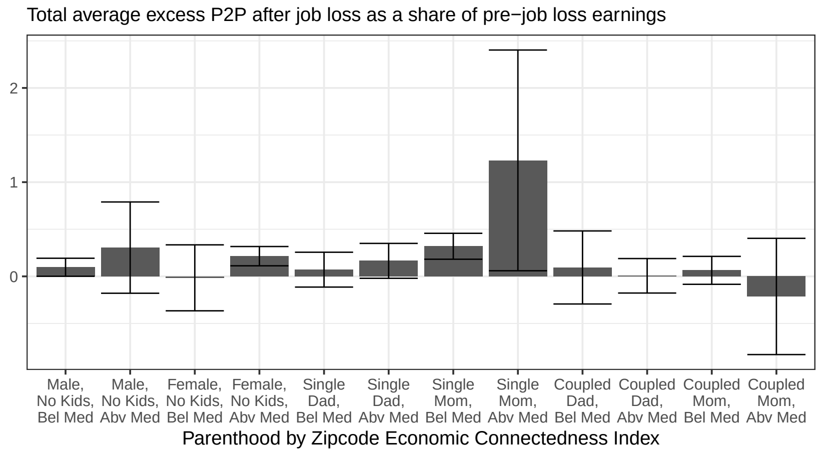
Parenthood by Economic Connectedness



Notes: Total P2P rep. rate after job loss calculated as sum of event study coefficients for relative months -1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

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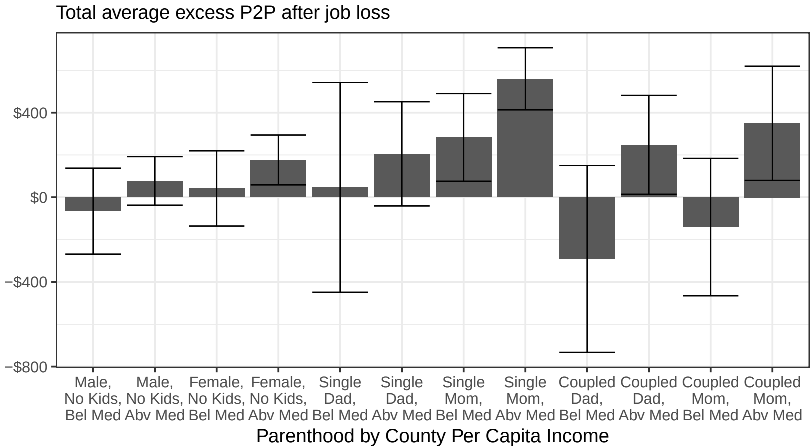
Parenthood by County Per Capita Income



Notes: Total excess P2P inflows after job loss calculated as sum of event study coefficients for relative months −1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

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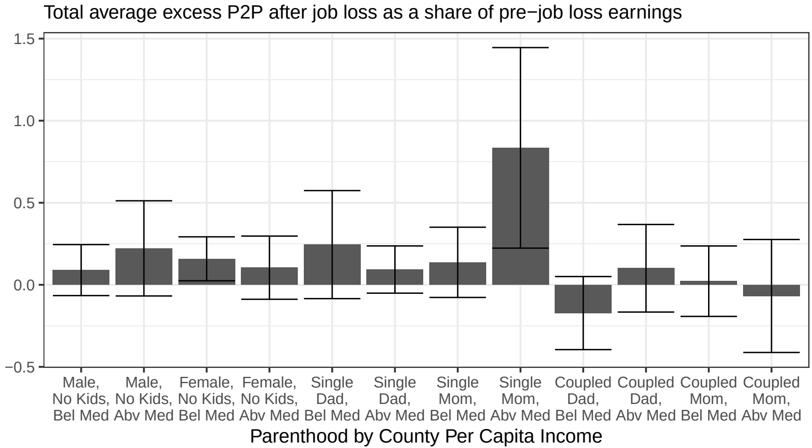
Parenthood by County Per Capita Income



Notes: Total P2P rep. rate after job loss calculated as sum of event study coefficients for relative months −1 to 10 interacted with group on x-axis. Family composition imputed from stimulus & CTC.

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Simple Welfare Model from Chetty and Saez (2010)

- Workers have ex ante unknown ability (or essentialness) n distributed $F(n)$
- Employed earn z and pay taxes τ and a private contract τ_p
- During unemployment, workers receive b and b_p
- Work if and only if $n > n^*$, and let $e = 1 - F(n^*)$

$$u(z - \tau - \tau_p) - u(b + b_p) = h(z/n^*)$$

- $n^*(b)$, and thus $e(b)$, is a function of b

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Deriving Welfare Money Metric

$$\max_b W(e) = eu(z - \tau - \tau_p) + (1 - e)u(z_L + b + b_p) - \Phi(e)$$

- First disutility of working, $\Phi(e)$ is increasing and convex in e

$$\Phi(e) = \int_0^\infty h(0)dF(n) + \int_{F^{-1}(1-e)}^\infty (h(z/n) - h(0))\, dF(n) = \int_{F^{-1}(1-e)}^\infty h(z/n)dF(n) + eh(0)$$

- Second let $b_p(b)$, so choosing b is the same as choosing $B = b + b_p$
- Differentiating wrt B yields

$$\frac{dW}{dB} = (1 - e)u'(c_e)\left[\frac{u'(c_u) - u'(c_e)}{u'(c_e)} - \frac{\varepsilon_{1-e,B}}{e}\right]$$

- By chain rule:

$$\frac{dW}{dB} = \frac{dW}{db} - \frac{dW}{db}\frac{db^p}{db} = (1 - r)\frac{dW}{db} \rightarrow \varepsilon_{1-e,B} = -(b + b_p)\frac{\frac{de}{dB}}{1 - e} = \left(1 - \frac{b_p}{b}\right)\frac{\varepsilon_{1-e,b}}{1 - r}$$

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Sufficient statistics welfare framework with k networks

- Workers have ex ante unknown ability n distributed $F^k(n)$ and utility $u(c) - h(z/n)$
  - Employed: earn z^k and pay tax τ^k and private contract τ_p^k
  - Unemployed: receive public and private benefits b^k and b_p^k
  - Crowd-out of b_p^k by b^k denoted $r^k = -db_p^k/db^k$
- Work if and only if $n > n^{*k} \to e^k = 1 - F_k(n^{*k})$ work, $\varepsilon_{1-e,b}^k$ is unemployment elasticity
- Government chooses b^k to maximize welfare, yielding the welfare money metric

$$G(b) = \sum_k p^k (1 - r^k) \left[\underbrace{\frac{u'(c_u^k) - u'(c_e^k)}{u'(c_e^k)}}_{\text{Marginal utility gap}} - \underbrace{\frac{\varepsilon_{1-e,b}^k}{e^k}}_{\text{Moral hazard}} \times \underbrace{\frac{1 + b_p^k/b^k}{1 - r^k}}_{\text{Crowd-out}} \right]$$

$$= \sum_k p^k (1 - r^k) \left[\left(\frac{c_e^k}{c_u^k} \right)^{\gamma^k} - 1 - \frac{\varepsilon_{1-e,b}^k}{e^k} \times \frac{1 + b_p^k/b^k}{1 - r^k} \right] \quad \text{under CRRA}$$

Back

Deriving Welfare Continued

Plugging in expressions for dW/db and $\varepsilon_{1-e,B}$ in terms of b and b_p yields

$$\frac{dW}{db} = (1-e)(1-r)u'(c_e)\left[\frac{u'(c_u)-u'(c_e)}{u'(c_e)} - \frac{\varepsilon_{1-e,b}}{e}\frac{1+b_p/b}{1-r}\right]$$

normalized into a money metric $G(b)$ by dividing by the dW/dz, the marginal welfare of an additional dollar of wages

$$\begin{aligned} G(b) &= \frac{dW}{db}\frac{1}{1-e}\bigg/ dW/dz\frac{1}{e} \\ &= (1-r)\left[\frac{u'(c_u)-u'(c_e)}{u'(c_u)} - \frac{\varepsilon_{1-e,b}}{e}\frac{1+b_p/b}{1-r}\right] \end{aligned}$$

Back

Excess P2P as a share of total insurance

- During unemployment what share of insurance made up by P2P?

- Impute excess P2P as the person-unemployment period fixed effect from the regression:

$$\text{P2P}_{it} = \lambda_t + \lambda_i \times \text{After job loss}_{it} + \lambda_i \times \text{Before job loss}_{it} + \epsilon_{it}$$
$$\text{where After job loss} \equiv 1\,(t + 1 \geq \text{Last Paycheck Month})$$
$$\text{Excess P2P} = \lambda_i \times \text{After job loss}_{it}$$

- These fixed effects measure average excess monthly P2P inflows after job loss

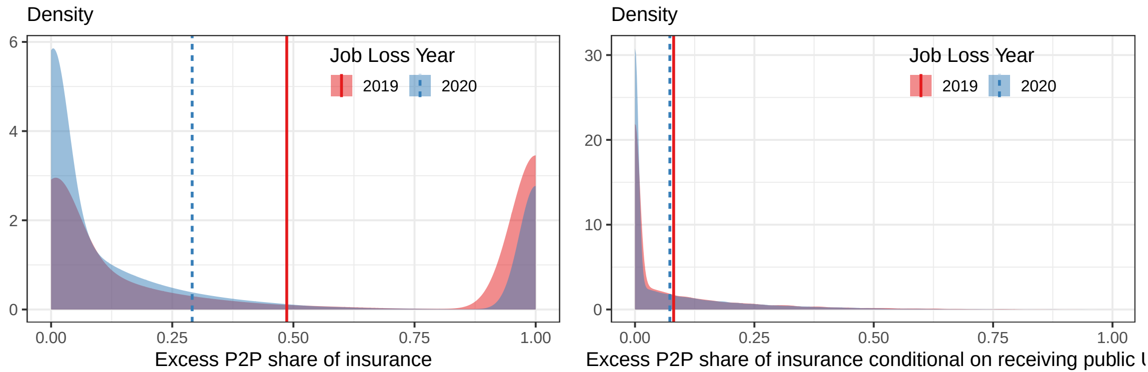
- Calculate excess P2P as a share of excess P2P plus average UI inflows:

$$\text{Excess P2P share} = \frac{\text{Excess P2P}}{\text{Excess P2P} + \text{UI}}$$

- Also calculate the raw total P2P share of total UI and P2P after job loss

Back

Density of Excess P2P during unemployment



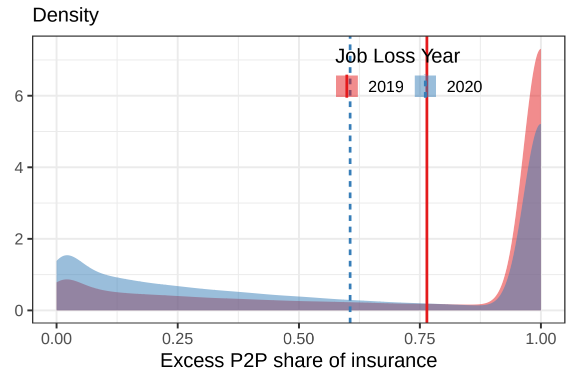
(a) Unconditional on UI receipt

(b) Conditional on UI receipt

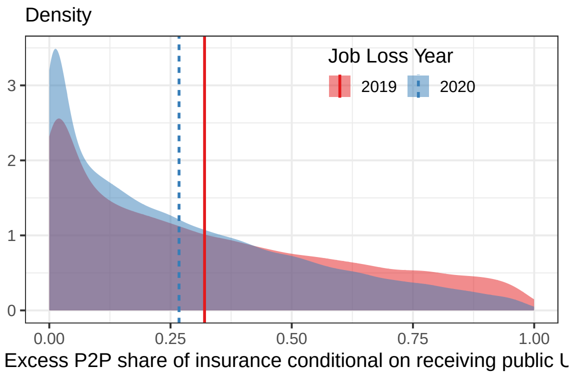
Notes: Share of P2P and UI inflows made up by P2P during unemployment. The excess share as calculated as the within user average increase in P2P inflows from a user-unemployment spell fixed effect. The denominator is average UI inflows in months receiving UI plus the excess P2P inflows.

Back

Density of Raw P2P during unemployment



(a) Unconditional on UI receipt

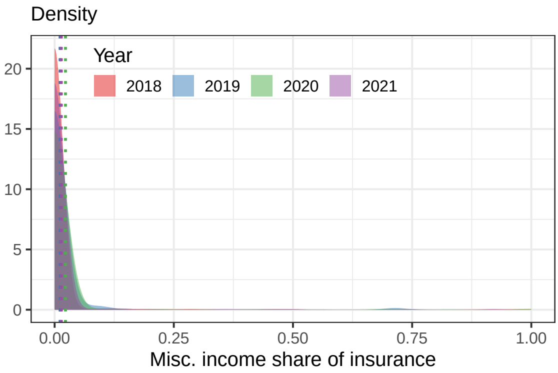


(b) Conditional on UI receipt

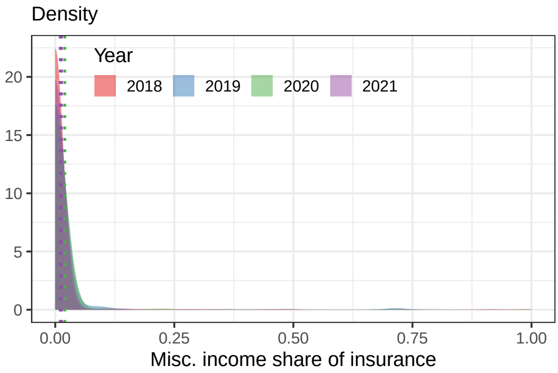
Notes: Share of P2P and UI inflows made up by P2P during unemployment. The numerator is the total P2P inflows after job loss and the denominator is total UI inflows and P2P inflows after job loss.

Back

Density of P2P from Survey of Income and Program Participation



(a) Friend share of friend gifts and UI



(b) Friend share of friend gifts and all formal UI

Notes: Share of insurance made by gifts from friends where formal insurance is just public UI (a) or formal insurance includes workers compensation, union UI, and company insurance.

Back

Measuring P2P inflows and outflows

- Financial services company Plaid categorizes transactions into 104 groups including Venmo, PayPal, Chase QuickPay with Zelle, and Square Cash
- Categories inconsistently applied over sample period
- Add regular expression searches of memos for P2P platforms
- Remove memos mentioning sales, bank fees, Earnin, gig platforms, or taxes
- Include transactions between \$5 and \$15,000 (untaxed maximum for family gifts)

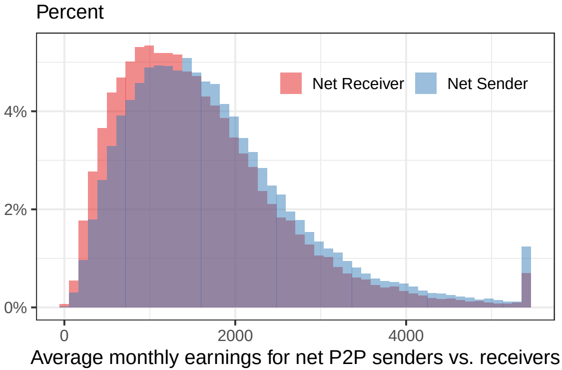
Categorizing transactions P2P flows timeline

Monthly Flows by Select Platforms

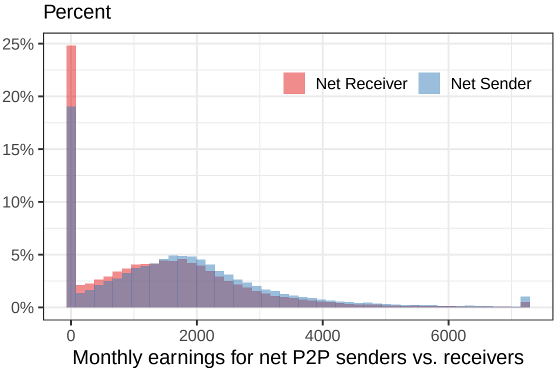
	All memos			Non-purchase memos		
	Mean	Median	SD	Mean	Median	SD
Outflow Venmo	58.33	0.00	253.99	58.12	0.00	253.42
Inflow Venmo	43.45	0.00	235.93	43.40	0.00	235.80
Outflow Paypal	32.11	0.00	265.08	30.40	0.00	261.63
Inflow Paypal	15.38	0.00	337.61	14.99	0.00	336.59
Outflow Zelle	191.38	0.00	605.46	186.95	0.00	602.68
Inflow Zelle	158.51	0.00	592.28	154.53	0.00	585.97
Outflow Cashapp	165.35	0.00	498.38	117.99	0.00	421.73
Inflow Cashapp	75.05	0.00	337.34	63.93	0.00	312.22
Outflow P2P Other	31.24	0.00	250.50	24.26	0.00	229.91
Inflow P2P Other	25.74	0.00	247.50	21.56	0.00	235.64
Outflow Any P2P	479.95	150.00	931.80	419.28	90.00	889.51
Inflow Any P2P	328.13	40.50	913.92	307.65	24.62	895.88
Observations	12299359			12299359		

Table: Sum stats of outflows and inflows of various platforms. P2P flows timeline

Monthly earnings by P2P net sender



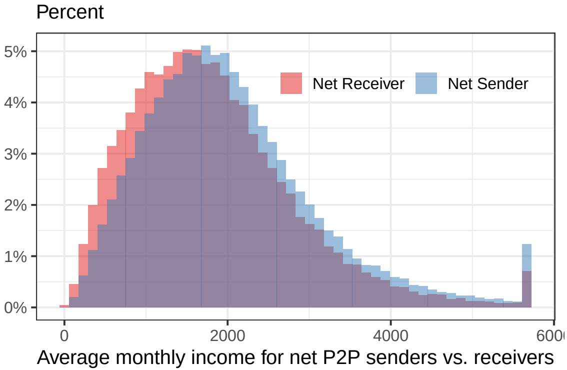
(a) Monthly Average



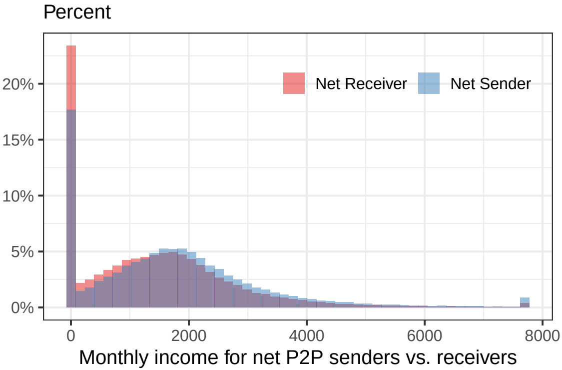
(b) March 2020

Notes: Histogram of monthly earnings by whether the user is a net sender or receiver of P2P in the relevant period. Figure (a) is monthly average earnings by whether user is an average sender or receive. Figure (b) is March earnings by whether the user is a net sender or receive of P2P.

Monthly income by P2P net sender



(a) Monthly Average

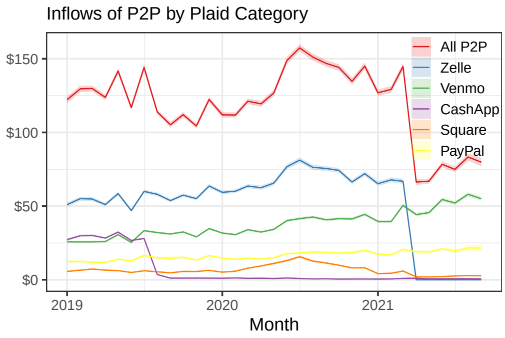


(b) March 2020

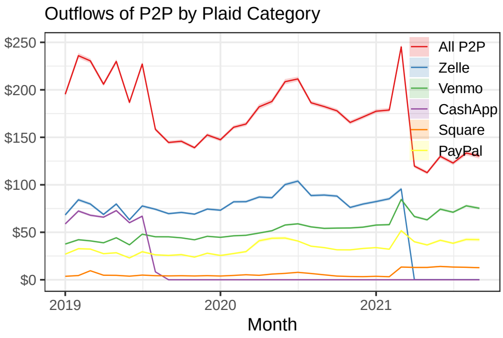
Notes: Histogram of monthly income by whether the user is a net sender or receiver of P2P in the relevant period. Figure (a) is monthly average income by whether user is an average sender or receive. Figure (b) is March income by whether the user is a net sender or receive of P2P.

P2P flows timeline Main Event Study

Plaid Timeline



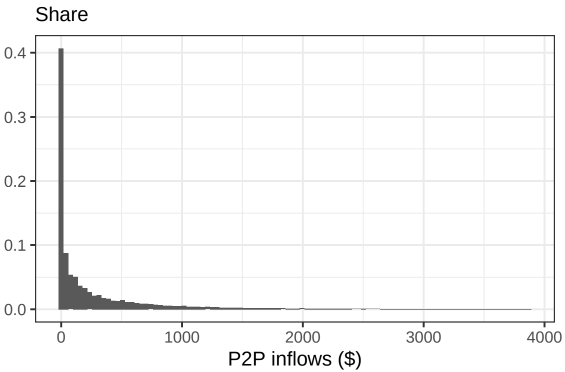
(a) Inflows



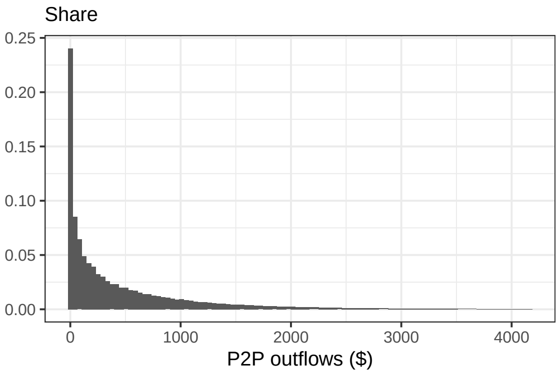
(b) Outflows

Notes: P2P inflows and outflow of transactions betweene $5 and $15,000, not linked to purchases, gig platforms, or stimlus payments over time.

Histograms of P2P flows



(a) Inflows ($)



(b) Outflows ($)

Notes: Histograms of user-monthly P2P inflows and outflows as well as transaction counts in the analysis sample.

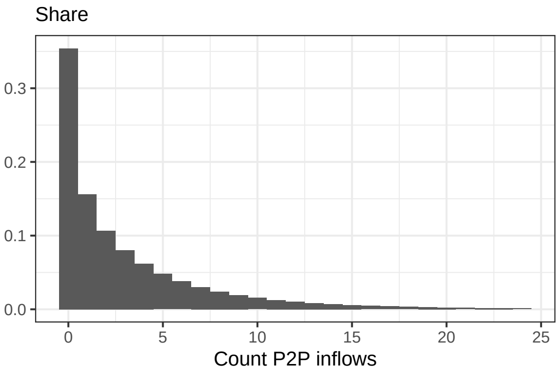
P2P flows timeline Categorizing transactions

Benchmarking Against Plaid Categories

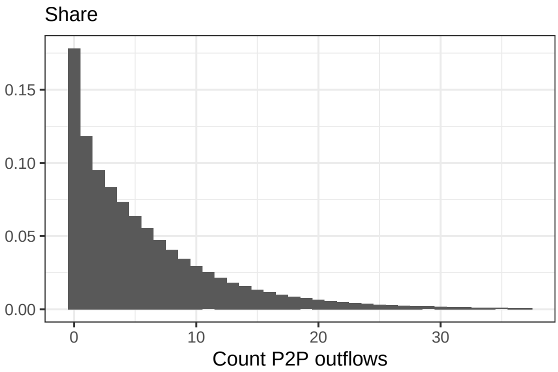
- Plaid is a fintech company that aims to categorize transactions using natural language processing
- They specifically flag: Cashapp (as Square Cash), PayPal, Venmo, and Chase Pay
- I want to use more categories than these five, but can use these to benchmark my reular expression flagging
- I also have checked event studies of these categories, which broadly follow the same patterns (not shown today)

P2P flows timeline

Histograms of P2P counts



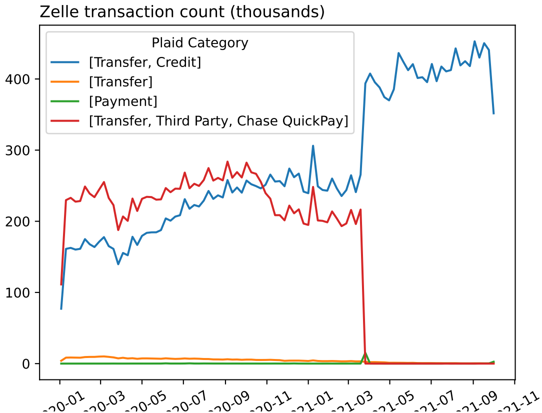
(a) Inflows Count



(b) Outflows Count

Notes: Histograms of user-monthly P2P inflows and outflows as well as transaction counts in the analysis sample.

Chase Quickpay with Zelle disapears



Notes: Isolating common categories associated with memos containing "ZELLE" around early 2021. The drop off in [Transfer, Third Party, Chase QuickPay], suggests that Plaid abandoned the category in late 2021.

Categorizing transactions | P2P flows timeline

Flagging P2P platforms with regular expressions

- Use regular expressions to flag bank memos like these:
- Venmo
  - VENMO**MICHAEL BEST* NEW YORK CITY NY DATE *XXXXXXXXXXXXXX*
  - VENMO DEPOSIT
  - POS DEP - VENMO**BRUNO FURTADO* NEW YORK NYUS - CARD ENDING IN *XXXX*
- Zelle
  - ZELLE TRANSFER CONF*XXX*: *RICARDO POMMER MUÑOZ*
  - *XXXXXXXX* - ZELLE: *EDDIE SHORE*
  - GAZELLE BUY & GO
- PayPal
  - PAYPAL TO *ANDREW OLENSKI* FROM *KYLE COOMBS*[2]
  - PAYPAL PURCHDATE *XXXXX*
- Xoom, Square Cash, Apple Pay, ChasePay, Chime, Facebook, GooglePay, CashApp
- A general "P2P" memo catchall

Categorizing transactions P2P flows timeline

Conditional DiD

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events conditional on using service

Method	OLS			IV		
Policy Change	March Delays	July Expiration	June Withdrawal	March Delays	July Expiration	June Withdrawal
	(1)	(2)	(3)	(4)	(5)	(6)
UI Inflows	0.01**	0.02***	0.07***	0.003	0.08***	0.08
	(0.006)	(0.007)	(0.02)	(0.009)	(0.02)	(0.05)
Standard-Errors	User		State	User		State
Lower bound × \$100 in UI	-0.01514	0.42752	3.2769	-1.5723	3.7655	-2.3216
Observations	16,552	16,708	16,110	16,552	16,708	16,110
R^2	0.00022	0.00161	0.00218	8.63×10^{-5}	-0.01733	0.00212
Month fixed effects	✓	✓	✓	✓	✓	✓

Difference-in-difference estimates of crowd-out of P2P Inflows on the extensive margin by unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic conditional on receiving P2P Inflows in both months.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV DID

Logged Outcomes IV DiD

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events

Method	OLS			IV		
Policy Change	March Delays	July Expiration	June Withdrawal	March Delays	July Expiration	June Withdrawal
	(1)	(2)	(3)	(4)	(5)	(6)
UI Inflows	-0.02***	-0.06**	0.002	-0.03***	-0.11***	-0.02
	(0.006)	(0.03)	(0.007)	(0.007)	(0.04)	(0.01)
Standard-Errors	User		State	User		State
Lower bound × \$100 in UI	0.86031	0.57783	0.94048	-4.5224	-18.244	-5.4330
Observations	34,508	31,746	28,546	34,508	31,746	28,546
R^2	0.79127	0.81560	0.80150	0.79124	0.81557	0.80125
F-test (1st stage), UI Inflows				96,543.0	45,168.0	4,680.8
User and Month fixed effects	✓	✓	✓	✓	✓	✓

Instrumental variable difference-in-difference estimates of crowd-out of logged P2P Inflows by logged unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV DID

Poisson Results

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events

Policy Change	March Delays (1)	July Expiration (2)	June Withdrawal (3)
UI Inflows	1.1×10^{-5}	-1.2×10^{-6}	$-1.8 \times 10^{-5**}$
	(1.3×10^{-5})	(1.4×10^{-6})	(8.7×10^{-6})
Standard-Errors	User		State
Lower bound $\times$ \$100 in UI	-0.00147	-0.00040	-0.00349
Observations	24,672	23,420	22,142
User and Month fixed effects	✓	✓	✓

Poisson estimates of crowd out of P2P Inflows on the extensive margin by unem

Extensive Margin of P2P Use

Table: Extensive margin of P2P Inflows by UI during various pandemic policy events

Policy Change	March Delays	July Expiration	June Withdrawal
	(1)	(2)	(3)
Post x Treat	-0.04***	0.02***	0.006
	(0.01)	(0.007)	(0.010)
Standard-Errors	User		State
Observations	34,508	31,746	28,546
R^2	0.76878	0.78695	0.77308
User and Month fixed effects	✓	✓	✓

Difference in difference estimates of crowd out of P2P Inflows on the exten

Crowd-out among single mothers

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events subset for single mothers

Method	OLS			IV		
Policy Change	March Delays	July Expiration	June Withdrawal	March Delays	July Expiration	June Withdrawal
	(1)	(2)	(3)	(4)	(5)	(6)
UI Inflows	0.01	-0.01	-0.05	0.01	-0.008	-0.005
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.08)
Lower bound $\times$ \$100 in UI	-2.0634	-5.3705	-11.056	-6.4292	-6.8373	-16.996
Observations	890	976	874	890	976	874
R^2	0.69884	0.83473	0.70411	0.69881	0.83472	0.70303
F-test (1st stage), UI Inflows				384.38	1,124.6	149.34
User and Month fixed effects	✓	✓	✓	✓	✓	✓

Instrumental variable difference-in-difference estimates of crowd-out of P2P Inflows by unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic. Subset for single mothers.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV DID

Crowd-out by county per capita income

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events subset by county income

Method	OLS						IV					
Policy Change	March Delays		July Expiration		June Withdrawal		March Delays		July Expiration		June Withdrawal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Median PCI	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
UI Inflows	0.01	0.003	-0.005***	0.005	0.04*	-0.02***	0.02	-0.0005	0.01	0.01	0.05	-0.06**
	(0.01)	(0.005)	(0.001)	(0.005)	(0.02)	(0.007)	(0.01)	(0.007)	(0.01)	(0.007)	(0.04)	(0.03)
Standard-Errors	User				State		User				State	
Lower bound $\times$ \$100 in UI	-1.0778	-0.61822	-0.79409	-0.47382	-0.04936	-3.2486	-1.0643	-1.5240	-1.1679	-0.33115	-3.0794	-11.416
Observations	5,328	29,170	4,774	26,962	3,880	24,650	5,328	29,170	4,774	26,962	3,880	24,650
R^2	0.69718	0.73365	0.79048	0.74886	0.78852	0.71054	0.69713	0.73363	0.78726	0.74884	0.78850	0.71007
F-test (1st stage), UI Inflows							4,764.8	23,051.2	253.06	30,543.1	578.11	4,388.6
User and Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Instrumental variable difference-in-difference estimates of crowd-out of P2P Inflows by unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic. Odd columns are users in counties below median per capita income and even columns are users in counties above median per capita income.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV DID

Crowd-out by economic connectedness

Table: Crowd-out of P2P Inflows by UI during various pandemic policy events subset by zip code economic connectedness

Method	OLS						IV					
Policy Change	March Delays		July Expiration		June Withdrawal		March Delays		July Expiration		June Withdrawal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Median EC	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above	Below	Above
UI Inflows	0.001	0.007	-0.004***	0.007	-0.01	-0.005	0.009	-0.006	0.003	0.02*	-0.04	-0.05*
	(0.006)	(0.007)	(0.002)	(0.008)	(0.01)	(0.01)	(0.008)	(0.01)	(0.009)	(0.01)	(0.03)	(0.03)
Lower bound × $100 in UI	-1.0276	-0.58516	-0.73841	-0.83940	-3.8987	-2.6662	-0.78436	-2.7197	-1.4980	-0.04394	-10.018	-10.622
Observations	15,578	18,130	15,152	15,808	13,600	14,204	15,578	18,130	15,152	15,808	13,600	14,204
R^2	0.71735	0.73948	0.74432	0.76086	0.73220	0.71034	0.71728	0.73930	0.74415	0.76078	0.73203	0.70965
F-test (1st stage), UI Inflows							13,922.2	13,228.4	2,019.6	17,238.9	2,788.4	2,008.7
User and Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Instrumental variable difference-in-difference estimates of crowd-out of P2P Inflows by unemployment insurance (UI) using different plausibly exogenous changes to UI benefits during the pandemic. Odd columns are users in counties below median economic connectedness and even columns are users in counties above median economic connectedness.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

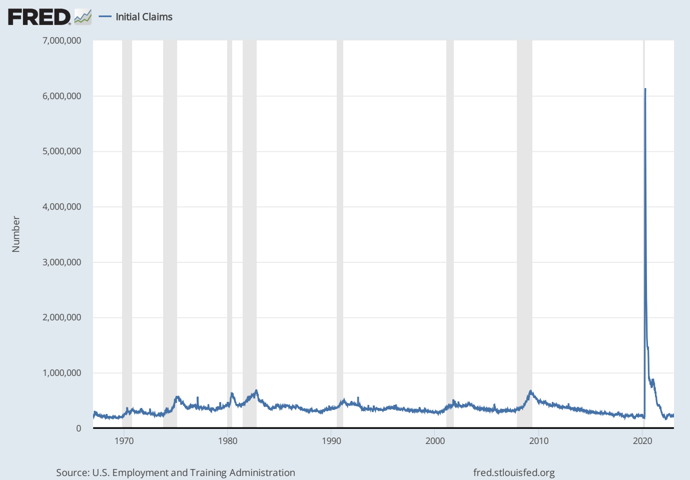
IV DID

Removing MPC

- Some P2P platforms are used to buy goods and services
- Use regular expressions to remove these types of transactions
  - Ex. Flag "POINT OF SALE" or "PURCHASE" or "DEBIT CARD WITHDRAWAL"
- Also, flag memos mentioning "EARNIN" as these represent Earnin app wage advances
- Tried removing payments that were not multiples of five as well – results remain largely unchanged

Back

Unprecedented spike in UI claims in Spring 2020



Timeline IV Diff-in-diff

Early Pandemic Delays Treatment and Control

$$y_{it} = \gamma \hat{\text{UI}} + \lambda_i + \lambda_t + \epsilon_{it}$$
$$\text{UI} = \beta(\text{April UI Receipt}) \times (\text{Month=May 2020}) + \lambda_i + \lambda_t + \nu_{it}$$

- Treatment group: March 2020 job losers that receive UI in April
- Control group: March 2020 job losers that receive UI in June
- Pre-period: March 2020
- Post-Period: May 2020

Timeline IV Diff-in-diff March Cohorts

July 2020 expiration of \$600

$$y_{it} = \gamma \hat{\text{UI}} + \lambda_i + \lambda_t + \epsilon_{it}$$
$$\text{UI} = \beta(\text{UI receipt by June 19}) \times (\text{Month=August 2020}) + \lambda_i + \lambda_t + \nu_{it}$$

- Treatment group: March 2020 job losers that receive UI by June
- Control group: Those unemployed after December 2020
- Pre-period: June 2020
- Post-Period: August 2020

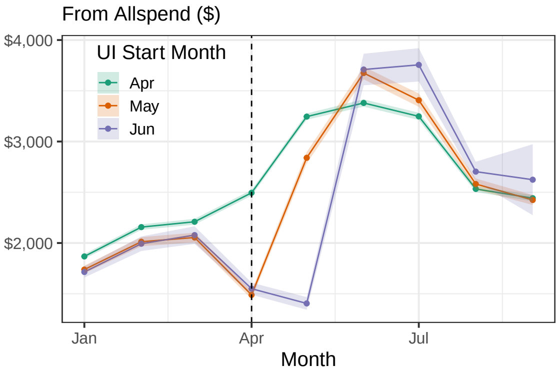
June 2021 early withdrawal from expanded UI benefits by 19 states

$$y_{it} = \gamma \hat{\mathrm{UI}} + \lambda_i + \lambda_t + \epsilon_{it}$$
$$\mathrm{UI} = \beta(\text{Withdrawal State}) \times (\text{Month=August 2021}) + \lambda_i + \lambda_t + \nu_{it}$$

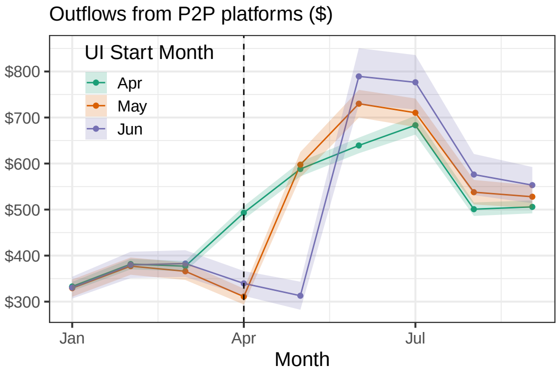
- Treatment group: Unemployed and insured workers in withdrawal states
- Control group: Unemployed and insured workers in retaining states
- Pre-period: April 2021 (announcement), Post-Period: August 2021

Timeline IV Diff-in-diff June Withdrawal

March Job Loser UI Receipt Cohorts



(a) Spending

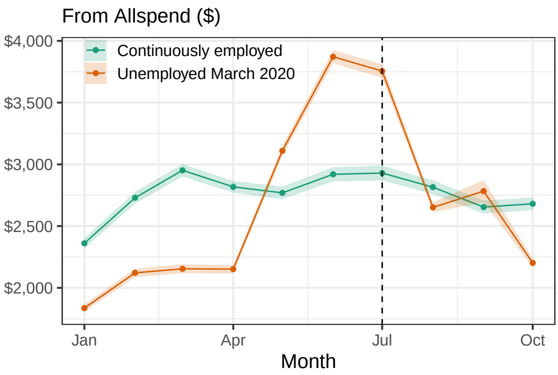


(b) P2P Outflows

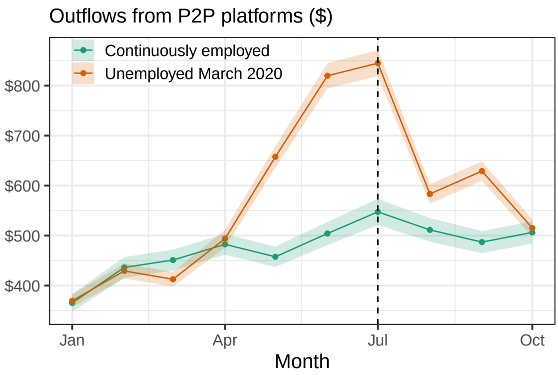
Notes: Subset of users that became unemployed at the end of March by month they receive UI.

Timeline Treatment Assignment Back

Unemployed and Insured vs. Unemployed after June 2020



(a) Spending

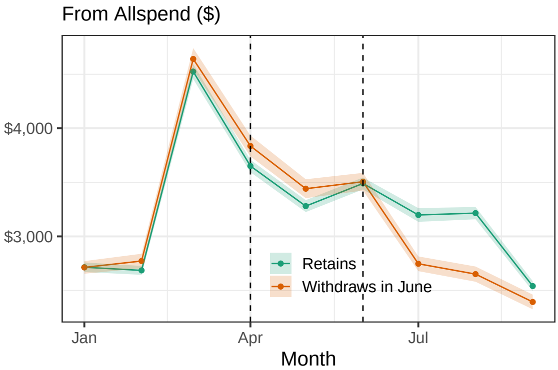


(b) P2P Outflows

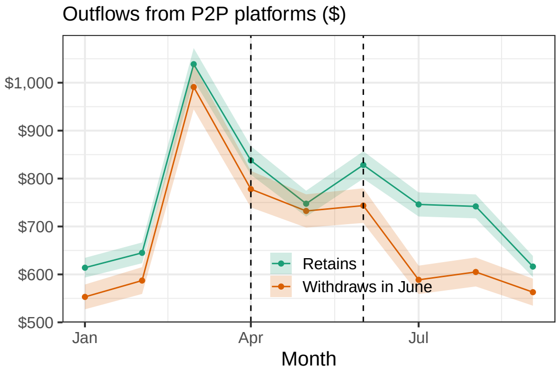
Notes: Subset of users that became unemployed at the end of March by month they receive UI.

Timeline Treatment Assignment Back

June 2021 Withdrawal Cohorts



(a) Spending

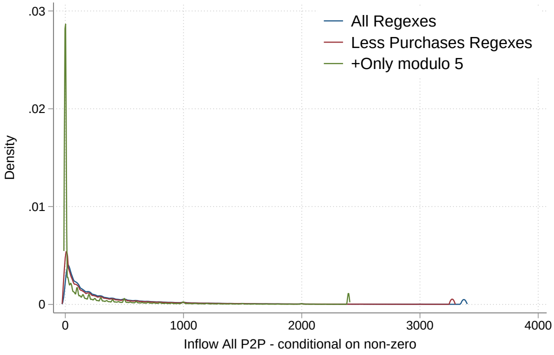


(b) P2P Outflows

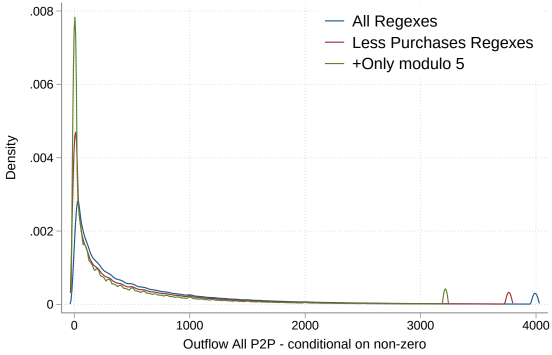
Notes: Event studies of the June/July UI expiration. Sample includes those unemployed and insured on April 30, the omitted data. Inverse probability weighting by quintile of UI start date.

Timeline Treatment Assignment Back

Removing "sale" memos & non-modulo 5 amounts



(a) Inflows



(b) Outflows

Notes: Distribution of monthly amounts do not change much after removing purchase memos or those transaction amounts not divisible by 5. Densities are conditional on non-zero in a month.

Back

Mock dataset example: Measuring P2P inflows and outflows

Amount	Date	Memo	Plaid Category
-$93.13	2/1/2020	Jimmy John's Order	Purchase, Restaurant
$25.00	1/19/2020	Zelle transfer from Kyle	Third Party, Chase QuickPay
$0.05	1/1/2020	Zelle transfer	Third Party, Chase QuickPay
$25.00	1/1/2020	Zelle transfer for Babysitting	Third Party, Chase QuickPay
$25.00	3/19/2021	Zelle transfer from Kyle	Uncategorized
$25.00	1/5/2020	PayPal for Etsy Sale 9999	Third Party, PayPal
-$25.00	3/17/2020	Venmo	Third Party, Venmo
$15,000	3/13/2020	CashApp Transfer	Third Party, Square Cash

Table: Mock transactions dataset showing how memos, Plaid categories, amounts of money and dates were used to flag P2P transactions.

Mock dataset example: Measuring P2P inflows and outflows

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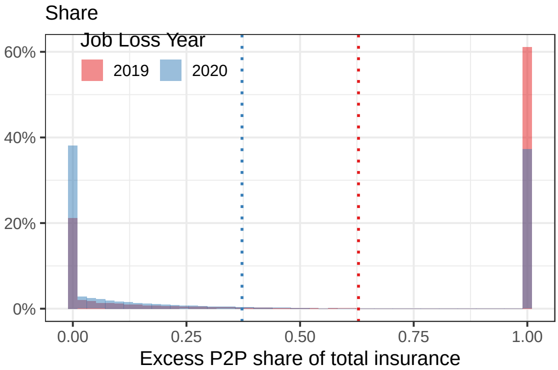
Table: Mock transactions dataset showing how memos, Plaid categories, amounts of money and dates were used to flag P2P transactions.

P2P platforms and their regexes

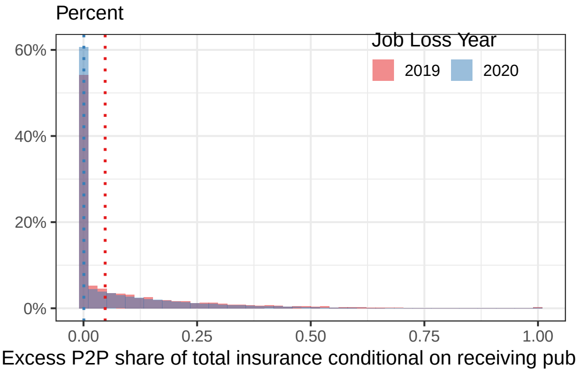
Platform	Regular Expression
Venmo	VENMO—VENM
PayPal	PAYPAL
Zelle	ZELLE
Square Cash App	SQC*CASH, SQUARE CASH, CASH APP
Apple Pay	APPLE PAY
Chase Pay	CHASEPAY, CHASE.*QUICK.*PAY
P2P	P2P, PERSON.*TO.*PERSON,PERSON.*2.*PERSON, P.*TO.*P
Google Pay	GOOGLE.*PAY
Facebook	PAY.FB.COM, FACEBOOK
Moneysend	MONEY.*SEND
Cashout	CASHOU?T?

Table: Types of P2P Platforms and their regexes. Back

Benchmarking P2P by year



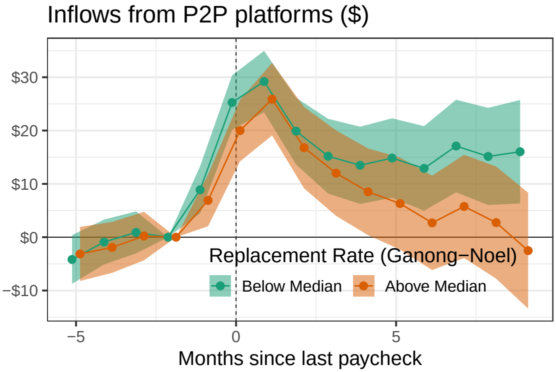
(a) Unconditional on UI



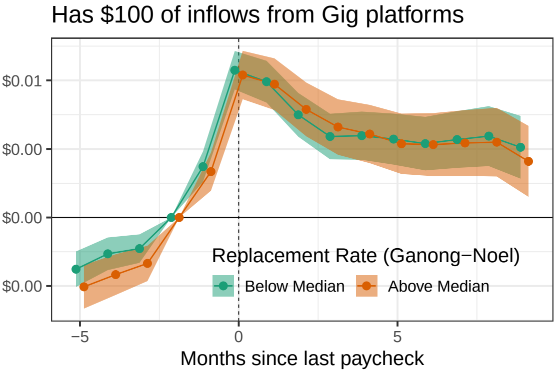
(b) Conditional on UI

Notes: Share of P2P and UI inflows made up by P2P during unemployment.

Religious Adherents Back



(a) Inflows

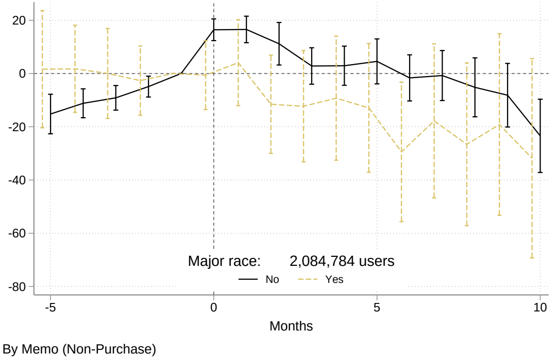


(b) Outflows

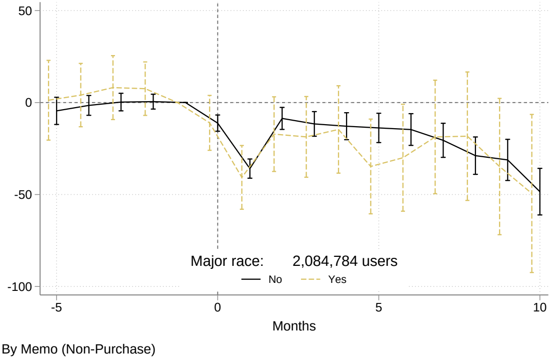
Notes: By whether state's replacement rate is above or below the median per Ganong-Noel calculations.

Zip Code Has A Majority Race

Back



(a) Inflows



(b) Outflows

Notes: Event study of inflows and outflows of any P2P platform around an unemployment event by whether zip code has a majority race per the 2010 Census counts. Data courtesy of IPUMS.

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