Evaluation*

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Contents

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Abstract

Neat and succinct abstract right here...

1 Introduction

2 Methods

2.1 Dataset

- Money Dashboard can access up to three years of historic data for each account a user links to their account.
- Each user for whom we have sufficient data thus serves as both a treatment unit and a potential control unit.
- Limitations: We have more data for users that signed up later. So average user in the study is not the average MDB user. If time of signup is mainly driven by financial savyness, then study sample is closer to overall population than MDB sample (if we rank groups as early joiners > late joiners > never joiners in terms of financial sophistication). If, however, signup reflects something like openness to newness, then it's not necessarily correlated with financial savyness. Either way, we might ignore it for now. We could test whether behaviour differs between early or late adopters, but that doesn't seem important enough.

2.2 Data preprocessing

Cleaning MDB cleaning (mdb/mdb/clean.py)

- About 75 percent of transactions are not automatically categorised, and we drop transactions that have no automatic tag. Dropping untagged transactions means that we might underestimate spending and savings, but entures that we do not miscategorise transactions.
- Custom tag classifications.
- Drop transactions for which user ID, account ID, date, amount, and transaction description are identical. This will drop some genuine transactions, such as someone buying two identical cups of coffees at the same coffee shop on the same day. However, data inspection suggests that in most cases, we remove genuine duplicates.

Sample selection We select our sample so as to include users for whom we can be reasonably certain that we observe all relevant financial transactions, and do so for at least six months before and after they sign up to the app. In addition to that, we exclude users who might use the app for business purposes as well as pensioneers, whose financial objectives might be different.

Table 1 lists the precise conditions we applied to implement these criteria and their effect on sample size. We remove the first and last month of data for all users because we are unlikely to

Table 1: Sample selection

	Users	User-months	Txns	Txns (m£)
Raw sample	271,856	7,948,520	662,112,975	124,573
Drop first and last month	265,760	7,406,482	643,851,490	121,098
Drop test users	264,698	7,338,506	637,863,549	119,436
App signup after March 2017	81,309	1,981,147	181,596,348	34,993
At least 6 months of pre and post signup data	37,961	1,085,215	107,354,457	22,153
At least one savings account	26,412	753,505	78,015,160	17,252
At least one current account	25,675	734,952	76,340,243	16,994
At least £5,000 of annual income	11,379	323,729	36,380,564	7,895
At least 10 txns each month	10,237	291,337	33,455,079	7,305
At least £200 of monthly spend	8,945	253,547	30,189,093	6,667
No more than 10 active accounts	8,143	224,986	25,427,757	4,945
Complete demographic information	6,876	192,606	21,855,775	4,189
Working age	6,739	188,324	21,498,631	4,033
Final sample	6,739	188,324	21,498,631	4,033

Notes: Number of users, user-months, transactions, and transaction volume in millions of British Pounds left in our sample after each sample selection step. Link to sample selection code: .

observe all transactions for these months. We also drop test users, since their objectives for app use might have been different from ordinary users.[1]

To ensure that we observe users for at least 12 months around app signup, we require 6 months of data before the signup month, and another five months after the signup month. Our main outcome variable is netflows into a user's savings accounts. It is thus critical that we observe enough historical data for these savings accounts to ensure that we observe all transactions during our 12 month perdiod of interest. This is complicated by the fact that we cannot see when an account was opened at the bank, but only when it was added to the app. While cases where a user adds an account to the app as soon as it was opened are unproblematic, users will often add accounts after they were opened, either because they have accounts that they opened before signing up to the app, or because they opened new accounts after signup but add them to the app with a delay. In such cases, it is critical that, once the account is added, we observe the complete historical data up to 6 months before signup or up to the month in which the account was opened, whichever happened later. To see why this is critical, imagine a scenario where a user opens an account 10 months before they sign up to the app, makes a monthly transfter to the account of £100, adds the account to the app on signup, but we onserve only 3 months of historical data. In this case we would observe that the user saved £300 before signup and £600 after, and erroneously conclude that post signup savings were twice as high. The most extreme case we need to cover is that of a user opening a savings account more than six months before signup and adding the account to the app five months after signup, in which case we need to be sure to observe 12 months of historical data. As shown in Appendix B, all major banks started providing 12 months of historical data for current and savings accounts from April 2017 onwards, which is why we restrict our sample to users who signed up in or after that month.

[1] We cannot identify test users precisely, but drop users who signed up prior to or during the first year the app was in operation.

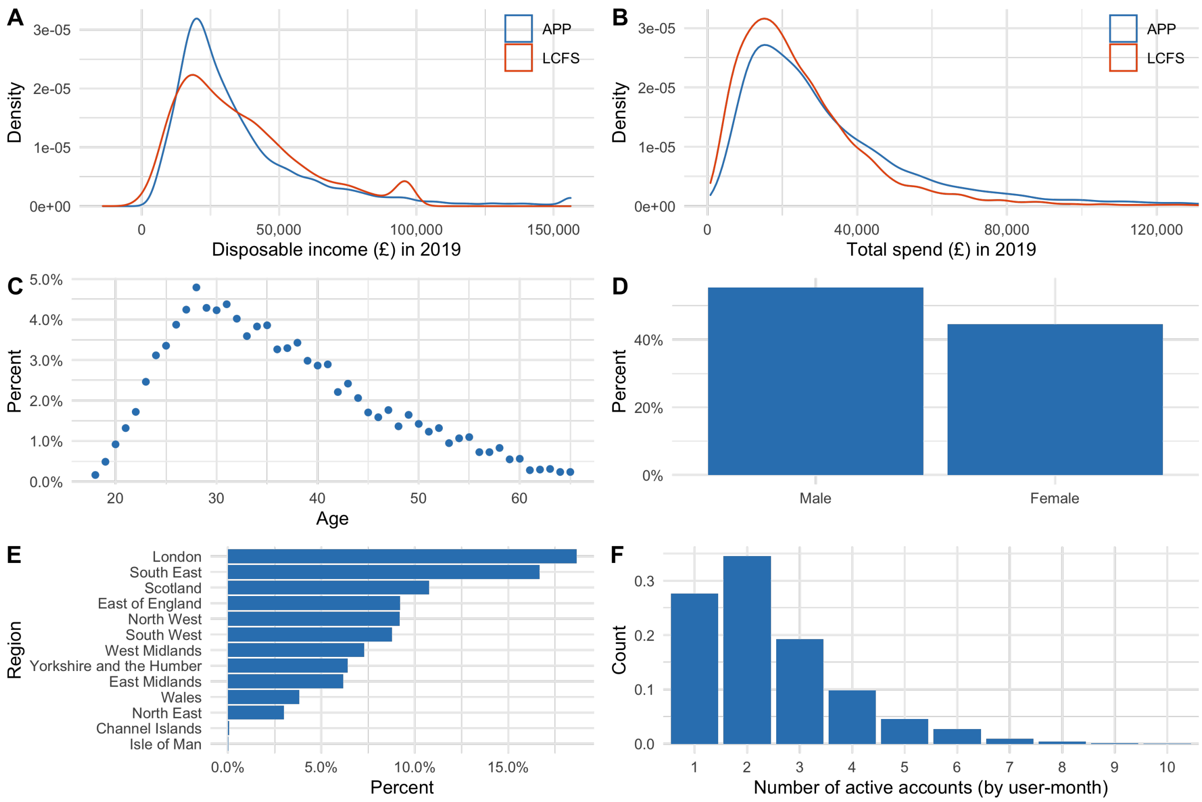
To ensure that we can be reasonably certain to observe users have added all their financial accounts to the app, we restrict our sample to users with at least one savings and current account, with an annual income of at least £5,000, and a minimum of 10 transactions and a spend of £200 every month. To remove users who might use the app for business purposes, we drop users with more than 10 active accounts in any given month. Finally, we remove users for whom we cannot observe all demographic information we use as covariates in our analysis, and users who are not between the ages of 18 and 65, as their financial objectives are plausibly different.

Data transformations: To minimise the influence of outliers, we winsorise spend, income, and savings accounts flow variables at the 1 percent level or – if we winsorise on both ends of the distribution – at the 0.5 percent level.

2.3 Summary statistics

Figure 1 describes the sample.

Figure 1: Sample characteristics



Notes: Panels A and B show the distribution of disposable income and total spending in 2019, respectively, benchmarked against the 2018/19 wave of the ONS Living Cost and Food Survey (LCFS). The remaining panels show the data distributions of age, gender, region, and the number of active accounts.

Table 2 provides summary statistics.

Table 2: Summary statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
user_id	504,257.1	34,391.8	442,639	475,685	500,741	529,551	575,009
ym	587.2	9.9	560	580	588	595	606
ymn	201,854.6	86.0	201,609	201,805	201,901	201,908	202,007
month	6.5	3.5	1	3	6	9	12
txns_count	113.3	60.4	10	70	102	143	332
txns_volume	18,361.4	26,224.6	256.2	6,073.4	10,381.0	18,934.2	185,464.6
month_income	2,967.2	2,294.2	417.3	1,521.1	2,256.5	3,612.6	13,490.9
inflows	761.1	2,545.1	0.0	0.0	0.0	400.0	19,732.5
outflows	753.1	2,436.4	0.0	0.0	0.0	370.0	18,250.4
netflows	17.0	2,961.7	−20,000.0	0.0	0.0	50.0	22,900.4
netflows_norm	−0.002	1.1	−7.6	0.0	0.0	0.02	7.8
inflows_norm	0.3	0.9	0.0	0.0	0.0	0.2	6.8
outflows_norm	0.3	0.9	0.0	0.0	0.0	0.2	6.9
has_pos_netflows	0.3	0.5	0	0	0	1	1
pos_netflows	422.7	2,143.4	0.0	0.0	0.0	50.0	22,900.4
user_reg_ym	590.9	5.3	581	587	591	595	601
t	0.4	0.5	0	0	0	1	1
tt	−3.7	11.1	−35	−10	−3	4	25
month_spend	2,751.0	2,625.2	200.1	1,202.6	1,987.0	3,293.2	17,050.0
age	36.7	10.1	18	29	35	43	65
is_female	0.4	0.5	0	0	0	1	1
is_urban	0.8	0.4	0	1	1	1	1
region_code	4.0	3.2	0	1	4	6	13
has_savings_account	1.0	0.0	1	1	1	1	1
has_current_account	1.0	0.0	1	1	1	1	1
generation_code	2.6	0.7	1	2	3	3	4
prop_credit	0.1	0.2	0.0	0.0	0.0	0.1	1.0
discret_spend	859.3	749.1	0.0	365.4	653.8	1,108.9	4,239.7
accounts_active	3.3	1.8	1	2	3	4	10
accounts_total	5.9	2.8	2	4	5	8	19

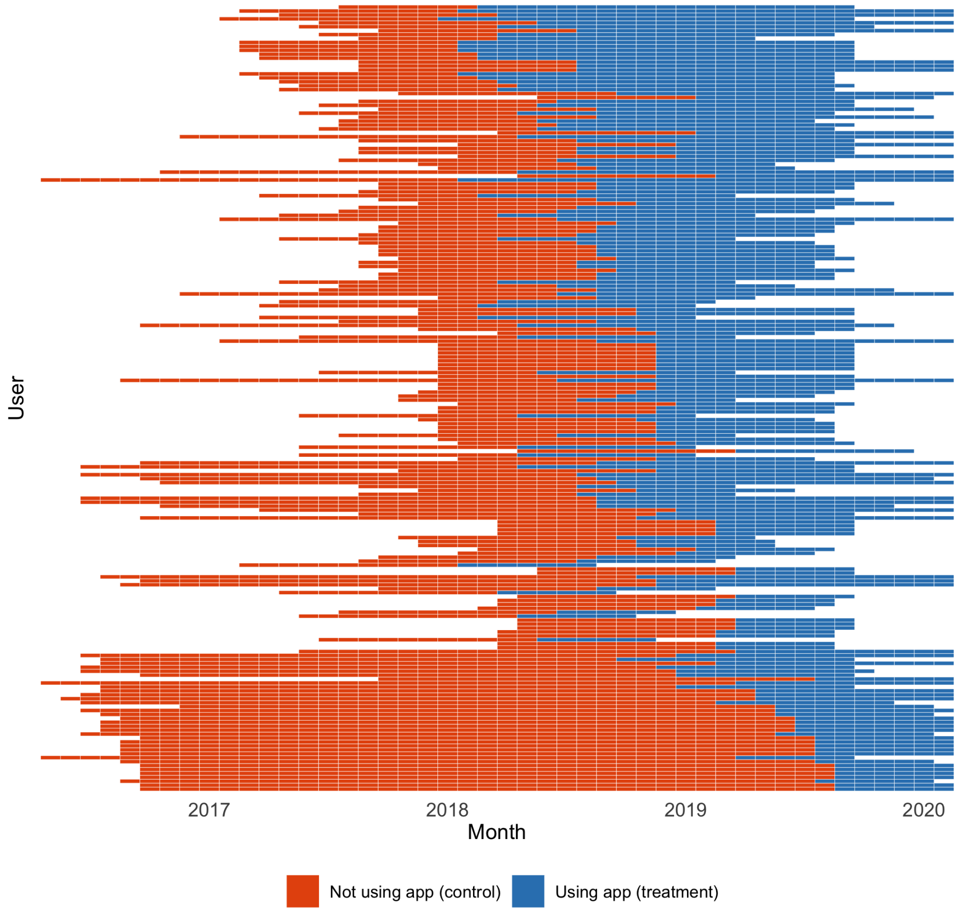
We use data from the 2018-2019 wave of the Office of National Statistics' Living Costs and Food Survey (LCFS).[2] Data covers the period between April 2018 and March 2019.

2.4 Treatment

A user changes treatment status from untreated to treated when they start using the app. Figure 2 shows the treatment history for 200 randomly selected users.

[2]We accessed the data via the UK Data Service at the following url: https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=8686.

Figure 2: Treatment assignment plot



Notes: Each horizontal line shows the observed pre and post signup periods in blue and red, respectively, for one of 200 randomly selected users. The faint vertical white lines indicate month borders, whitespace indicates periods in which we do not observe the user. To the left of the observed period, this is because the app cannot access data before that point when the user signs up; to the right, because they have stopped using the app.

2.5 Outcomes

Savings... see Table 3 for details.

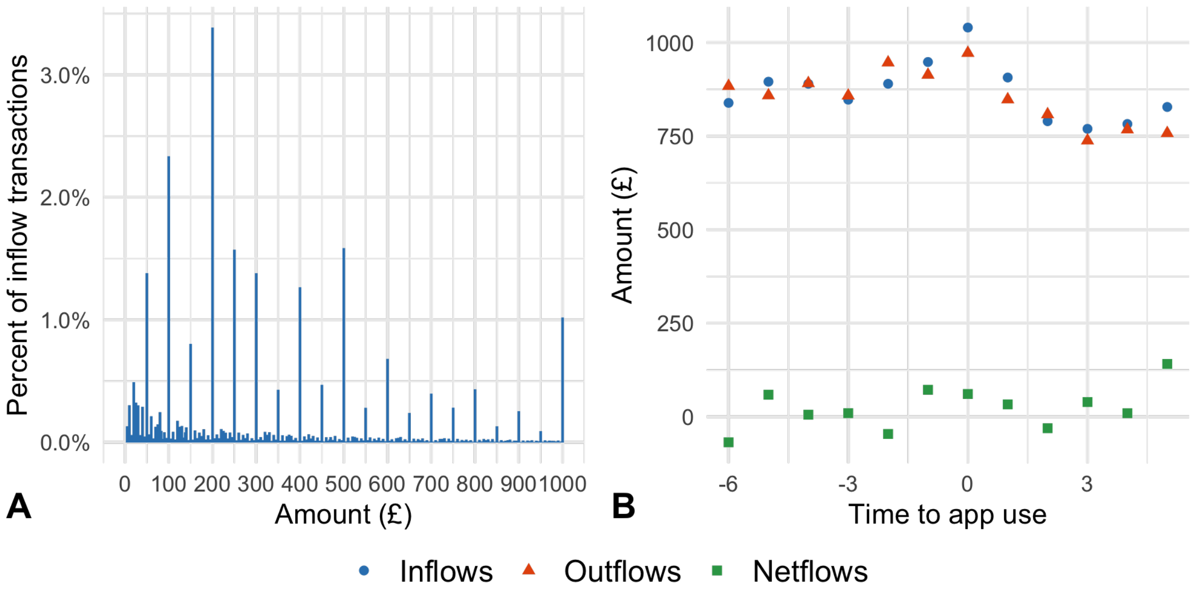
For a more nuanced understanding of how app use affects savings we also consider net-savings – total savings account inflows minus outflows – as a proportion of monthly income to see whether a willingness to save more might be offset by a (later) need to withdraw funds, and a dummy variable for whether a user has any savings account inflows in a given month to see whether the app helps users save at all. To investigate possible channels, we consider total spend, highly discretionary spend, banking charges, the total amount of borrowing, as well as payday borrowing, all as proportion of monthly income.

Net savings (*netflows_ norm*) Inflows into minus outflows out of all of a user's savings accounts divided by monthly income. To capture only "user-generated" flows, we exclude interest and "save the change" transactions, as well as transactions of less than £5 in absolute value. Monthly income and raw inflows and outflows are winsorised at the 1 percent level. We focus on net inflows to capture effective savings.

Positive net savings dummy (*has_pos_netflows*) Dummy equal to 1 if there were positive net savings (as defined above). Captures extensive margin of savings (change in number of months with positive net deposits)

Positive net savings (*pos_netflows*) Equal to net savings if there were positive net savings. Captures intensive margin of savings (change in deposit amount in months with positive net deposits)

Figure 3: Savings patterns



Notes: Panel A shows distribution of savings account inflow amounts, making clear that most transactions are the kinds of round amounts we would expect savings transactions to be. The data is truncated at £1000. Panel B hows inflows, outflows, and netflows into savings accounts for six months before and five months after app use.

Adjusting for multiple hypothesis tests We think of our secondary outcomes as exploratory and do not make any adjustments for multiple hypothesis testing.[3] An alternative approach, based on Anderson (2008), would be to group outcomes into "savings", "spending", "borrowing", and "fees", and consider them as different dimensions of a latent variable of interest which we might call "financial management skills". We do not do that for two reasons: first and foremost, because we think it is natural to think of the amount saved as the ultimate outcome and of other outcomes as providing a more nuanced understanding of savings behaviour or as suggesting possible channels through which app use affects savings. Thinking of savings as the main goal is also reflected in Money Dashboard's main promise, which is to help users spend less and save more, as shown in Figure 9. Second, as pointed out in Carlin et al. (2017), incurring overdraft fees is not an unambiguous sign of a financial mistake, as the opportunity to go into overdraft confers a benefit to the consumer.[4]

[3]For a recent game-theoretically motivated discussion of when and how to correct for multiple hypothesis testing, see Viviano et al. (2021).

[4]For further discussions on fees, see Jørring (2020) and Stango and Zinman (2009).

2.6 Covariates

We control for baseline behaviour, events, and personal characteristics that, to various degrees, capture a person's need, capacity, motivation, and awareness to save. Table 3 lists all covariates used together with their definition and the rationale for including them. For all variables, we include contemporaneous values as well as lags for up to 6 periods. In addition, we control for the previous six months of savings to capture time-invariant unobserved drivers of savings behaviour (in specifications without fixed effects) as well as a possible signal for a higher or lower need for future savings.

Following VanderWeele (2019) we include covariates that affect either outcomes or the propensity for treatment or both, exclude from this set of variables those that are instruments (affect the outcome only through their effect on treatment propensity) and add to it proxies for unobserved variables that are a common cause of both outcomes and treatment propensity.[5]

The table below describes the construction and rationale for including of all variables used. The code used to construct the variables is available on GitHub.

Table 3: Covariates

Variable (name in dataset)	Definition	Rationale
	Primary outcome	
	Covariates	
New loan dummy (*new_loan*)	Dummy variable equal to 1 if user takes out a new loan. Calculated positive inflows of funds tagged as "loan".	Might increase (additional funds) or decrease (need to repay) propensity to save in month of takeout and lower propensity to save in the future due to need to repay.
Unemployment benefits dummy (*unemp_benefits*)	Dummy variable equal to 1 if user has inflow of funds tagged as "job seeker benefits".	Might lower a user's ability to save but increase their need for a money management app.
Monthly income (*month_income*)	Average monthly income in a calendar year, calculated as the sum of all credits tagged income payments in said year divided by 12.	Income may alter the need and ability to save and correlate with cognitive characteristics that alter a person's propensity to use a money management app.

2.7 Estimation

We choose a window from -6 to 5 for two reasons: because the longer a window we consider, the less plausible our ceteris paribus assumption is, and the longer the window, the smaller our sample.

2.8 Code access

We provide links to code that creates key elements of the paper such as variable definitions and sample selection directly in the relevant places in the paper so they can be accessed conveniently. The links are indicated with the GitHub logo, . The hope is that this helps the curious reader

[5] VanderWeele (2019) calls this the "modified disjunctive cause criterion" for covariate selection, as it includes the set of variables that are causally related to either outcomes, or treatment propensity, or both, but modified to account for potential bias by excluding instruments and including proxies of unobserved causes of both outcomes and treatment.

clarify questions about subtleties they might have while reading the paper. The complete projects GitHub repo is at https://github.com/fabiangunzinger/mdb_eval.

3 Results

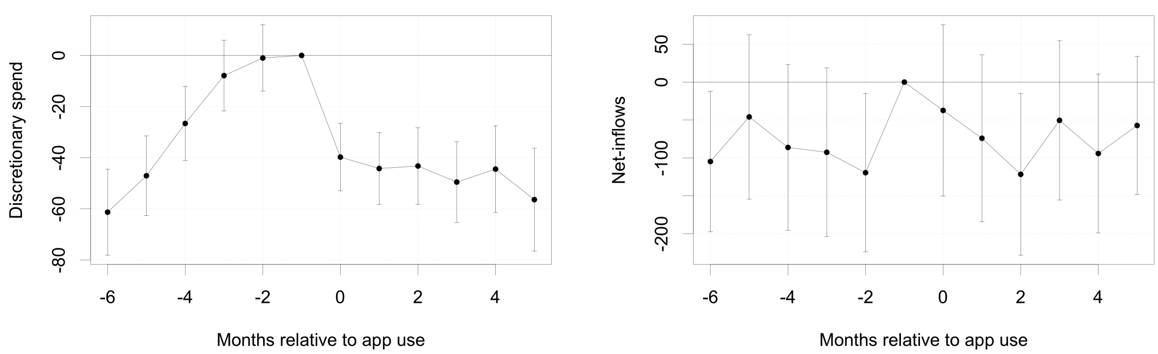
3.1 Dynamic TWFE

$$y_{it} = \sum_{s=-6}^{5} \beta_s D_{it}^s + \alpha_i + \lambda_t + \gamma X_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} is the outcome for individual i at time t, α_i and λ_t are individual and year-month fixed effects, respectively, and X_{it} is a vector of individual and time varying controls. D_{it}^s equals 1 if, in period t, individual i is s months away from signing up to the app. The set of β_s coefficients measure the effect of treatment s periods away from treatment, which is what we are interested in.

To avoid multicollinearity issues and uniquely identify the lead and lag effects, we omit relative period indicator $s = -1$, and bin the endpoints of our observation window so that $D_{it}^{-6} = 1$ for all periods six or more periods prior to signup and $D_{it}^{5} = 1$ for all months five or more months after the month of signup. This expresses all estimates relative to the omitted period, which – given that it is the last month before signup – serves as a natural benchmark. Binning endpoints assumes that coefficients remain constant outside the observation window. Both of these approaches are standard in the literature, as discussed in Sun and Abraham (2021) and Schmidheiny and Siegloch (2019).

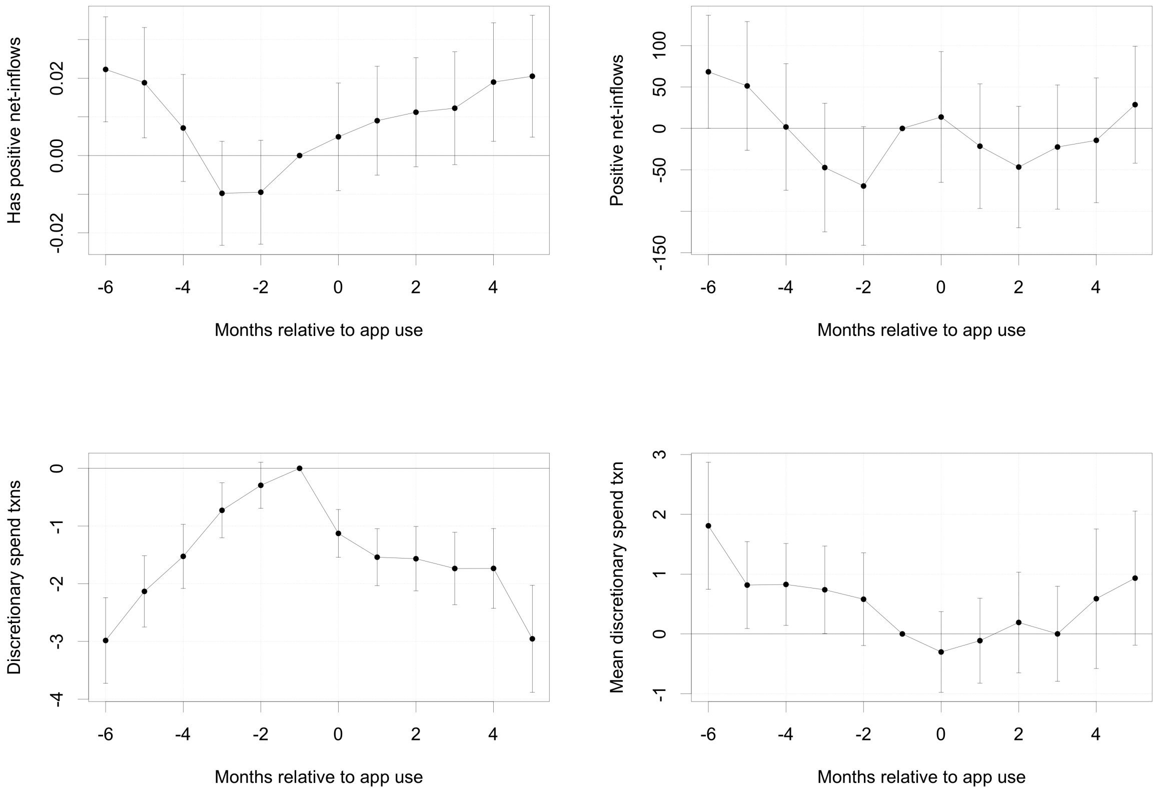
Figure 4: Main results



Notes: Figures show estimates of leads and lags frome estimating model (1) with distretionary spend (left) and netflows into savings accounts (right) as the dependent variable. Standard errors are clustered by user.

3.2 Decomposing intensive and extensive margins

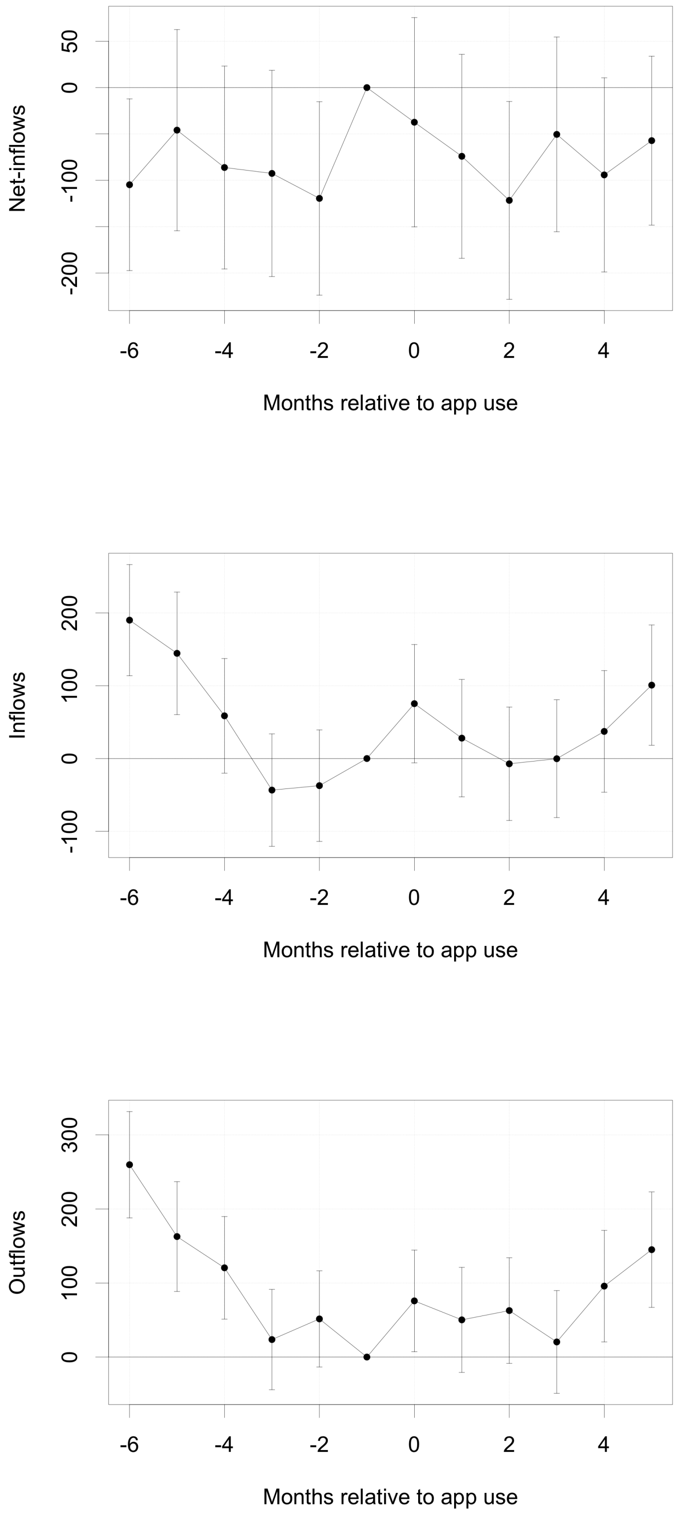
Figure 5: Decomposition of intensive and extensive margins



Notes: ...

3.3 Decomposing inflows and outflows

Figure 6: Decomposing inflows and outflows



Notes: ...

Table 4: Decomposing inflows and outflows

Dependent Variables:	Net-inflows	Inflows	Outflows
Model:	(1)	(2)	(3)
Variables			
Months relative to app use = -6	-104.79**	190.11***	259.80***
	[-197.45; -12.13]	[113.66; 266.56]	[187.96; 331.64]
Months relative to app use = -5	-45.90	144.54***	162.75***
	[-154.47; 62.67]	[60.37; 228.70]	[88.62; 236.88]
Months relative to app use = -4	-86.20	58.67	120.54***
	[-195.61; 23.21]	[-20.02; 137.37]	[51.23; 189.85]
Months relative to app use = -3	-92.58	-43.36	23.62
	[-203.84; 18.67]	[-120.62; 33.89]	[-44.16; 91.39]
Months relative to app use = -2	-119.53**	-37.28	51.52
	[-223.87; -15.19]	[-113.85; 39.30]	[-13.38; 116.42]
Months relative to app use = 0	-37.36	75.39*	75.86**
	[-150.33; 75.61]	[-5.93; 156.72]	[7.16; 144.56]
Months relative to app use = 1	-74.11	28.01	50.24
	[-184.14; 35.92]	[-52.74; 108.76]	[-20.73; 121.21]
Months relative to app use = 2	-121.66**	-7.26	62.77*
	[-228.41; -14.90]	[-85.19; 70.68]	[-8.57; 134.11]
Months relative to app use = 3	-50.48	-0.26	20.39
	[-155.51; 54.56]	[-81.18; 80.66]	[-48.99; 89.77]
Months relative to app use = 4	-94.18*	37.26	95.80**
	[-198.96; 10.59]	[-46.32; 120.84]	[20.47; 171.13]
Months relative to app use = 5	-57.21	100.83**	145.05***
	[-148.40; 33.97]	[18.23; 183.44]	[67.11; 223.00]
Month income	0.08***	0.06***	-0.01
	[0.05; 0.10]	[0.04; 0.09]	[-0.03; 0.02]
Month spend	-0.16***	0.10***	0.25***
	[-0.19; -0.14]	[0.08; 0.12]	[0.23; 0.26]
Active accounts	72.05***	306.25***	243.69***
	[56.26; 87.84]	[286.09; 326.40]	[224.27; 263.11]
Fixed-effects			
User ID	Yes	Yes	Yes
Year-month	Yes	Yes	Yes
Fit statistics			
Observations	188,324	188,324	188,324
R^2	0.04170	0.24635	0.31097
Within R^2	0.01007	0.03612	0.07191

Clustered (User ID) co-variance matrix, 95% confidence intervals in brackets
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.4 Static results

3.5 Additional TWFE specifications

Figure 7: Alternative model specifications

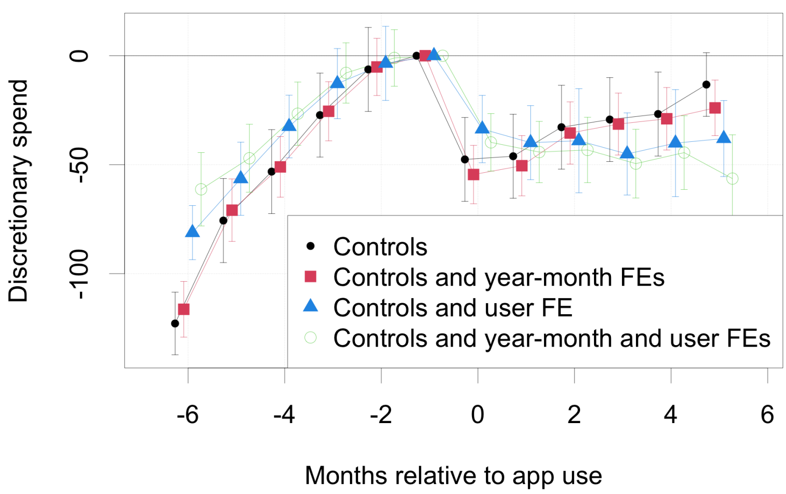


Table 5: Static results

Dependent Variables:	Net-inflows				Discretionary spend			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
App use	37.93***	27.14**	5.60	-0.08	69.09***	49.57***	1.05	-26.59***
	[11.16; 64.71]	[0.73; 53.55]	[-26.57; 37.78]	[-50.70; 50.55]	[63.78; 74.40]	[41.46; 57.69]	[-12.92; 15.03]	[-38.73; -14.4
Month income	0.07***	0.07***	0.07***	0.08***	0.02***	0.01***	0.02***	0.01***
	[0.06; 0.08]	[0.05; 0.10]	[0.05; 0.09]	[0.05; 0.10]	[0.02; 0.02]	[0.01; 0.02]	[0.02; 0.03]	[0.00; 0.02]
Month spend	-0.12***	-0.16***	-0.12***	-0.16***	0.16***	0.12***	0.16***	0.12***
	[-0.13; -0.11]	[-0.19; -0.14]	[-0.14; -0.10]	[-0.19; -0.14]	[0.16; 0.16]	[0.11; 0.12]	[0.15; 0.17]	[0.11; 0.12]
Active accounts	40.31***	75.54***	38.87***	73.25***	45.89***	85.71***	42.11***	74.92***
	[32.66; 47.95]	[60.63; 90.45]	[25.50; 52.23]	[57.69; 88.81]	[44.37; 47.40]	[81.21; 90.20]	[39.61; 44.60]	[70.47; 79.38
Intercept	-7.11				172.15***			
	[-37.67; 23.45]				[166.09; 178.21]			
Fixed-effects								
User ID		Yes		Yes		Yes		Yes
Year-month			Yes	Yes			Yes	Yes
Fit statistics								
Observations	188,324	188,324	188,324	188,324	188,324	188,324	188,324	188,324
R^2	0.00888	0.04113	0.00940	0.04163	0.41618	0.66171	0.42425	0.67060
Within R^2		0.01014	0.00877	0.01000		0.28046	0.40985	0.23849

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Alternative model specifications

Dependent Variable:	Discretionary spend			
Model:	(1)	(2)	(3)	(4)
Variables				
Months relative to app use = -6	-122.89***	-116.38***	-81.19***	-61.31***
	[-137.26; -108.52]	[-129.14; -103.61]	[-93.92; -68.47]	[-78.13; -44.48]
Months relative to app use = -5	-75.65***	-70.88***	-56.47***	-47.06***
	[-94.93; -56.37]	[-85.23; -56.54]	[-73.72; -39.23]	[-62.64; -31.47]
Months relative to app use = -4	-53.18***	-51.02***	-32.49***	-26.61***
	[-72.45; -33.91]	[-64.94; -37.10]	[-47.26; -17.72]	[-41.13; -12.09]
Months relative to app use = -3	-27.25***	-25.50***	-12.83	-7.89
	[-46.51; -7.98]	[-39.08; -11.91]	[-29.37; 3.72]	[-21.71; 5.94]
Months relative to app use = -2	-6.28	-5.15	-3.49	-1.01
	[-25.55; 12.98]	[-18.28; 7.98]	[-20.95; 13.98]	[-13.00; 11.97]
Months relative to app use = 0	-47.60***	-54.52***	-33.64***	-39.76***
	[-66.86; -28.34]	[-67.92; -41.12]	[-49.51; -17.76]	[-52.94; -26.58]
Months relative to app use = 1	-46.13***	-50.48***	-39.90***	-44.23***
	[-65.40; -26.86]	[-64.31; -36.65]	[-57.33; -22.47]	[-58.30; -30.15]
Months relative to app use = 2	-32.80***	-35.47***	-39.02***	-43.24***
	[-52.07; -13.53]	[-49.73; -21.20]	[-63.52; -14.51]	[-58.23; -28.24]
Months relative to app use = 3	-29.28***	-31.36***	-45.09***	-49.52***
	[-48.56; -10.01]	[-45.57; -17.15]	[-64.44; -25.75]	[-65.30; -33.74]
Months relative to app use = 4	-26.75***	-28.93***	-40.10***	-44.45***
	[-46.02; -7.47]	[-43.25; -14.60]	[-65.31; -14.89]	[-61.37; -27.53]
Months relative to app use = 5	-13.23*	-23.94***	-38.01***	-56.39***
	[-27.83; 1.37]	[-36.72; -11.16]	[-55.92; -20.11]	[-76.52; -36.27]
Month income	0.02***	0.01***	0.02***	0.01***
	[0.02; 0.03]	[0.01; 0.02]	[0.02; 0.03]	[0.00; 0.02]
Month spend	0.16***	0.12***	0.16***	0.12***
	[0.16; 0.16]	[0.11; 0.12]	[0.15; 0.17]	[0.11; 0.12]
Active accounts	41.94***	77.85***	40.80***	72.39***
	[40.39; 43.49]	[73.30; 82.41]	[38.37; 43.22]	[67.89; 76.88]
Intercept	274.97***			
	[260.03; 289.91]			
Fixed-effects				
User ID		Yes		Yes
Year-month			Yes	Yes
Fit statistics				
Observations	188,324	188,324	188,324	188,324
R^2	0.41828	0.66337	0.42491	0.67097
Within R^2		0.28398	0.41052	0.23935

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 8: Alternative model specifications

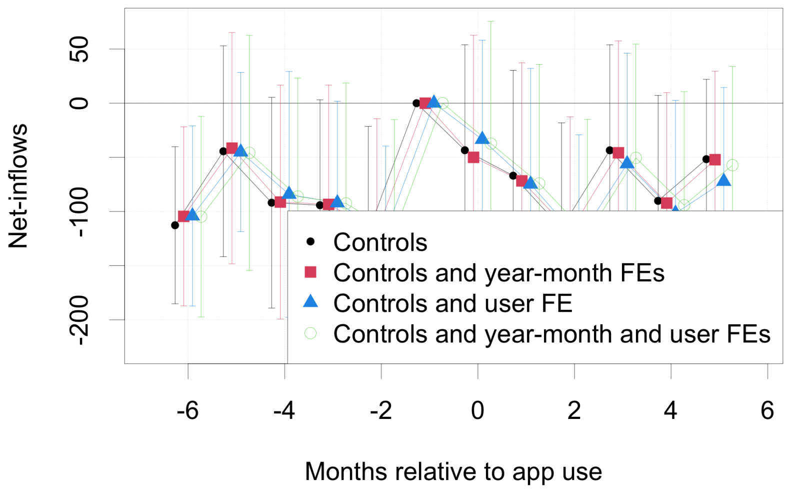


Table 7: Alternative model specifications

Dependent Variable:	Net-inflows			
Model:	(1)	(2)	(3)	(4)
Variables				
Months relative to app use = -6	-112.73***	-104.53**	-104.14**	-104.79**
	[-185.30; -40.15]	[-187.23; -21.82]	[-189.54; -18.75]	[-197.45; -12.13]
Months relative to app use = -5	-44.39	-41.53	-45.12	-45.90
	[-141.77; 52.99]	[-148.42; 65.37]	[-120.66; 30.41]	[-154.47; 62.67]
Months relative to app use = -4	-91.89*	-91.29*	-84.19	-86.20
	[-189.22; 5.44]	[-199.28; 16.69]	[-200.74; 32.37]	[-195.61; 23.21]
Months relative to app use = -3	-94.20*	-93.45*	-92.07*	-92.58
	[-191.50; 3.10]	[-203.59; 16.70]	[-188.41; 4.27]	[-203.84; 18.67]
Months relative to app use = -2	-118.68**	-118.36**	-119.19***	-119.53**
	[-215.98; -21.39]	[-222.44; -14.29]	[-200.97; -37.41]	[-223.87; -15.19]
Months relative to app use = 0	-43.44	-50.00	-33.48	-37.36
	[-140.74; 53.85]	[-162.78; 62.77]	[-127.72; 60.75]	[-150.33; 75.61]
Months relative to app use = 1	-66.94	-71.74	-74.79	-74.11
	[-164.24; 30.37]	[-180.80; 37.33]	[-184.62; 35.05]	[-184.14; 35.92]
Months relative to app use = 2	-115.51**	-118.47**	-125.25**	-121.66**
	[-212.82; -18.19]	[-224.24; -12.70]	[-224.00; -26.50]	[-228.41; -14.90]
Months relative to app use = 3	-43.50	-45.81	-56.03	-50.48
	[-140.83; 53.83]	[-149.17; 57.54]	[-161.02; 48.97]	[-155.51; 54.56]
Months relative to app use = 4	-90.18*	-92.22*	-101.71*	-94.18*
	[-187.52; 7.17]	[-194.27; 9.84]	[-208.92; 5.49]	[-198.96; 10.59]
Months relative to app use = 5	-51.70	-52.18	-72.25	-57.21
	[-125.43; 22.03]	[-133.90; 29.54]	[-161.36; 16.86]	[-148.40; 33.97]
Month income	0.07***	0.07***	0.07***	0.08***
	[0.06; 0.08]	[0.05; 0.10]	[0.05; 0.09]	[0.05; 0.10]
Month spend	-0.12***	-0.16***	-0.12***	-0.16***
	[-0.13; -0.11]	[-0.19; -0.14]	[-0.14; -0.10]	[-0.19; -0.14]
Active accounts	38.47***	72.54***	37.00***	72.05***
	[30.62; 46.31]	[56.98; 88.10]	[24.59; 51.40]	[56.26; 87.84]
Intercept	95.97**			
	[20.52; 171.42]			
Fixed-effects				
User ID		Yes		Yes
Year-month			Yes	Yes
Fit statistics				
Observations	188,324	188,324	188,324	188,324
R^2	0.00897	0.04121	0.00948	0.04170
Within R^2		0.01022	0.00885	0.01007

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.6 Subgroups

To analyse which groups benefit most from adopting Money Dashboard, we split our sample by gender, generation, income quartiles, and pre-adoption savings behaviour.

We define generations as follows: boomers were born between 1946 and 1964, Gen X between 1965 and 1980, Millennials between 1981 and 1996, and Gen Z after 1997.[6]

Subgroup analysis: same Fig an Tab as in main analysis, but with line for each subgroup. One figure for each of: gender, generations, income terciles, per-adoption average savings tercile (inspired by Carlin et al. (2017), see Fig 5 and Table 4).

See also section 6 in Gargano and Rossi (2021)

4 Discussion

Limitations:

- Can't say whether increase in savings was achieved by going into debt elsewhere

[6]Based on age ranges provides by Beresford Research.

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Anderson, Michael L (2008). "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects". In: *Journal of the American statistical Association* 103.484, pp. 1481–1495.

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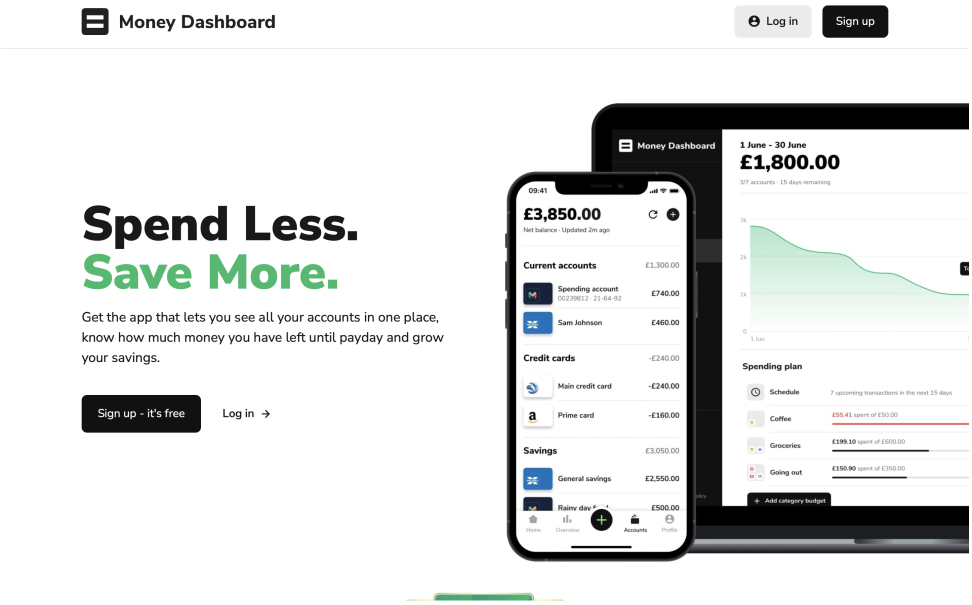
A Money Dashboard application

Figure 9: Money Dashboard website screenshot



Notes: Screenshot from the top of the Money Dashboard website, at moneydashboard.com, accessed on 29 April 2022.

B Data

B.1 Historical data availability

Translate jupyter notebook fig to R.

C Additional results

C.1 Additional TWFE specifications

Figure 10: Alternative model specifications

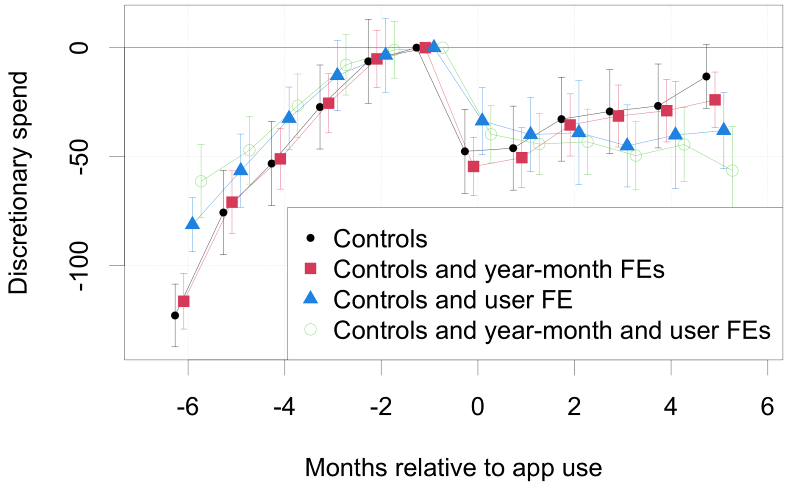


Table 8: Alternative model specifications

Dependent Variable:	Discretionary spend			
Model:	(1)	(2)	(3)	(4)
Variables				
Months relative to app use = -6	-122.89***	-116.38***	-81.19***	-61.31***
	[-137.26; -108.52]	[-129.14; -103.61]	[-93.92; -68.47]	[-78.13; -44.48]
Months relative to app use = -5	-75.65***	-70.88***	-56.47***	-47.06***
	[-94.93; -56.37]	[-85.23; -56.54]	[-73.72; -39.23]	[-62.64; -31.47]
Months relative to app use = -4	-53.18***	-51.02***	-32.49***	-26.61***
	[-72.45; -33.91]	[-64.94; -37.10]	[-47.26; -17.72]	[-41.13; -12.09]
Months relative to app use = -3	-27.25***	-25.50***	-12.83	-7.89
	[-46.51; -7.98]	[-39.08; -11.91]	[-29.37; 3.72]	[-21.71; 5.94]
Months relative to app use = -2	-6.28	-5.15	-3.49	-1.01
	[-25.55; 12.98]	[-18.28; 7.98]	[-20.95; 13.98]	[-13.00; 11.97]
Months relative to app use = 0	-47.60***	-54.52***	-33.64***	-39.76***
	[-66.86; -28.34]	[-67.92; -41.12]	[-49.51; -17.76]	[-52.94; -26.58]
Months relative to app use = 1	-46.13***	-50.48***	-39.90***	-44.23***
	[-65.40; -26.86]	[-64.31; -36.65]	[-57.33; -22.47]	[-58.30; -30.15]
Months relative to app use = 2	-32.80***	-35.47***	-39.02***	-43.24***
	[-52.07; -13.53]	[-49.73; -21.20]	[-63.52; -14.51]	[-58.23; -28.24]
Months relative to app use = 3	-29.28***	-31.36***	-45.09***	-49.52***
	[-48.56; -10.01]	[-45.57; -17.15]	[-64.44; -25.75]	[-65.30; -33.74]
Months relative to app use = 4	-26.75***	-28.93***	-40.10***	-44.45***
	[-46.02; -7.47]	[-43.25; -14.60]	[-65.31; -14.89]	[-61.37; -27.53]
Months relative to app use = 5	-13.23*	-23.94***	-38.01***	-56.39***
	[-27.83; 1.37]	[-36.72; -11.16]	[-55.92; -20.11]	[-76.52; -36.27]
Month income	0.02***	0.01***	0.02***	0.01***
	[0.02; 0.03]	[0.01; 0.02]	[0.02; 0.03]	[0.00; 0.02]
Month spend	0.16***	0.12***	0.16***	0.12***
	[0.16; 0.16]	[0.11; 0.12]	[0.15; 0.17]	[0.11; 0.12]
Active accounts	41.94***	77.85***	40.80***	72.39***
	[40.39; 43.49]	[73.30; 82.41]	[38.37; 43.22]	[67.89; 76.88]
Intercept	274.97***			
	[260.03; 289.91]			
Fixed-effects				
User ID		Yes		Yes
Year-month			Yes	Yes
Fit statistics				
Observations	188,324	188,324	188,324	188,324
R^2	0.41828	0.66337	0.42491	0.67097
Within R^2		0.28398	0.41052	0.23935

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 11: Alternative model specifications

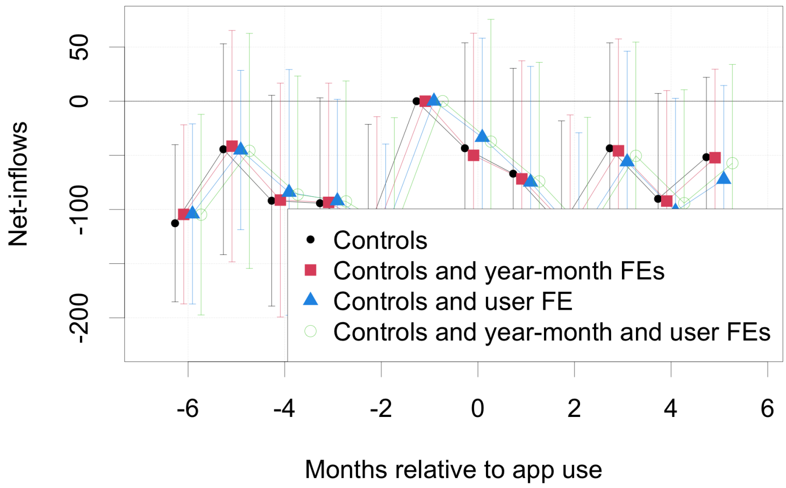


Table 9: Alternative model specifications

Dependent Variable:	Net-inflows			
Model:	(1)	(2)	(3)	(4)
Variables				
Months relative to app use = -6	-112.73***	-104.53**	-104.14**	-104.79**
	[-185.30; -40.15]	[-187.23; -21.82]	[-189.54; -18.75]	[-197.45; -12.13]
Months relative to app use = -5	-44.39	-41.53	-45.12	-45.90
	[-141.77; 52.99]	[-148.42; 65.37]	[-120.66; 30.41]	[-154.47; 62.67]
Months relative to app use = -4	-91.89*	-91.29*	-84.19	-86.20
	[-189.22; 5.44]	[-199.28; 16.69]	[-200.74; 32.37]	[-195.61; 23.21]
Months relative to app use = -3	-94.20*	-93.45*	-92.07*	-92.58
	[-191.50; 3.10]	[-203.59; 16.70]	[-188.41; 4.27]	[-203.84; 18.67]
Months relative to app use = -2	-118.68**	-118.36**	-119.19***	-119.53**
	[-215.98; -21.39]	[-222.44; -14.29]	[-200.97; -37.41]	[-223.87; -15.19]
Months relative to app use = 0	-43.44	-50.00	-33.48	-37.36
	[-140.74; 53.85]	[-162.78; 62.77]	[-127.72; 60.75]	[-150.33; 75.61]
Months relative to app use = 1	-66.94	-71.74	-74.79	-74.11
	[-164.24; 30.37]	[-180.80; 37.33]	[-184.62; 35.05]	[-184.14; 35.92]
Months relative to app use = 2	-115.51**	-118.47**	-125.25**	-121.66**
	[-212.82; -18.19]	[-224.24; -12.70]	[-224.00; -26.50]	[-228.41; -14.90]
Months relative to app use = 3	-43.50	-45.81	-56.03	-50.48
	[-140.83; 53.83]	[-149.17; 57.54]	[-161.02; 48.97]	[-155.51; 54.56]
Months relative to app use = 4	-90.18*	-92.22*	-101.71*	-94.18*
	[-187.52; 7.17]	[-194.27; 9.84]	[-208.92; 5.49]	[-198.96; 10.59]
Months relative to app use = 5	-51.70	-52.18	-72.25	-57.21
	[-125.43; 22.03]	[-133.90; 29.54]	[-161.36; 16.86]	[-148.40; 33.97]
Month income	0.07***	0.07***	0.07***	0.08***
	[0.06; 0.08]	[0.05; 0.10]	[0.05; 0.09]	[0.05; 0.10]
Month spend	-0.12***	-0.16***	-0.12***	-0.16***
	[-0.13; -0.11]	[-0.19; -0.14]	[-0.14; -0.10]	[-0.19; -0.14]
Active accounts	38.47***	72.54***	37.00***	72.05***
	[30.62; 46.31]	[56.98; 88.10]	[24.59; 51.40]	[56.26; 87.84]
Intercept	95.97**			
	[20.52; 171.42]			
Fixed-effects				
User ID		Yes		Yes
Year-month			Yes	Yes
Fit statistics				
Observations	188,324	188,324	188,324	188,324
R^2	0.00897	0.04121	0.00948	0.04170
Within R^2		0.01022	0.00885	0.01007

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*