Spending profiles predict savings*

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September 21, 2022

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*We are grateful to Redzo Mujcic and and Zvi Safra for helpful comments. The research was supported by Economic and Social Research Council grant number ES/V004867/1. WBS ethics code: E-414-01-20. Gunzinger: Warwick Business School, fabian.gunzinger@warwick.ac.uk; Stewart: Warwick Business School, neil.stewart@wbs.ac.uk.

1 Introduction

This paper documents variations in spending profiles and payments into emergency savings for a large set of users of a financial management app and shows that spending profiles predict emergency savings.

We define emergency savings as inflows into savings accounts. These savings will be made up of savings for particular goals – a new car, a holiday, a wedding – and savings directed towards building up a buffer for financial emergencies. Because in our data we cannot distinguish between these two cases, we refer to all of them as emergency savings.[1] These short-term savings are distinct from long-term savings aimed to build up funds for retirement, either through individually owned pension and investment vehicles or employer-linked pension schemes. Both kinds of saving are important for financial well-being, yet while there is a large literature on pension savings, little is known about how people save for the short-term.[2]

Studying the determinants of emergency savings is important because around a quarter of adults in the UK and the US are unable to cover irregular expenses like car and medical bills: In the UK, 25 percent of adults would be unable to cover an unexpected bill of £300 (Philipps et al. 2021), while in the US, about 30 percent would be unable to cover a $400 bill (Governors of the Federal Reserve System 2022). Similarly, resarch in the UK has shown that having £1000 in savings reduces by more than half a household's chances of falling into debt that leads to financial problems (Philipps et al. 2021).

Studying spending profiles is of interest because:

- Our understanding of how people spend their money is based on survey data.
- Large-scale transaction-level data offers the possibility to study spending behaviour based on real-time data that are automatically collected for a large number of users. Such data has only become available ver recently and have not, thus far, been used to investigate systematically how people spend their money.
- Research in psychology suggests that disorder is maladaptive and associated with

[1] MDB allows users to create custom tags and some users use them to indicate the intended use for their savings transactions (e.g. "wedding", "holidays"). But only a very small number of transactions have such tags, and we do not pursue this further.

[2] Well-documented behavioural biases that help explain undersaving for pensions are, among others, present bias (Laibson 1997, Laibson and Marzilli-Ericson 2019), inertia (Madrian and Shea 2001), over-extrapolation (Choi et al. 2009), and limited self-control and willpower (Thaler and Shefrin 1981, Benhabib and Bisin 2005, Fudenberg and Levine 2006, Loewenstein and O'Donoghue 2004, Gul and Pesendorfer 2001). One danger of viewing low savings mainly as a result of behavioural biases is that while these biases likely do play some role and designing environments and tools to help correct them are thus part of the solution, it is at least conceivable that this is an area where the focus on behaviour-level solutions distracts from an effort to find more effective society-level solutions, a danger inherent in behavioural science research convincingly highlighted in Chater and Loewenstein (2022): if the main problem is that many people are unable to earn enough to save, then the effectiveness of helping them manage their low incomes more effectively pales in comparison with efforts to help them earn more.

a range of negative outcomes such as impaired executive function (Vernon-Feagans et al. 2016), lower cognitive inhibition (Mittal et al. 2015), and activation of anxiety-related neural circuits (Hirsh et al. 2012). In the study of human behaviour, more chaotic behaviour has been found to predict the a higher number of visits to and higher spend in supermarkets (Guidotti et al. 2015), higher calorie intake (Skatova et al. 2019) and financial distress (Muggleton et al. 2020).

We hypothesise that less predictable spending patterns are associated with a lower probability for making payments into emergency savings accounts. Possible channels:

- Disorder (personal life or environment): leads to more impulsive shopping behaviour and makes forgetting to save more likely.
- Scarcity: life challenges focus attention away from deliberate shopping, causing hore impulse purchases, and make fortetting to save more likely.

What we do:

- Systematically documenting emergency savings patterns.
- Systematically documenting variation in spending profiles.
- Showing that unpredictability in spending profiles is associated with lower emergency savings.

Contribution to literatures:

- Understanding emergency savings behaviour (nest, aspen reports), (Sabat and Gallagher 2019) for sources on short-term savings literature, Colby and Chapman (2013) for lit on savings goals. See Colby and Chapman (2013) has useful literature review on short-term savings and suggests that subgoals can increase willingness to forego short-amounts in the present because they move the reference point in a prospect-theory framework. Philipps et al. (2021) present results from an employer-linked initiative that offers employees to have a portion of their salary automatically transferred into a savings pot. Policy literature: (CAN 2019, CFPB 2017, MPS 2018). Older literature:Savings lit: Lunt and Livingstone (1991) and Oaten and Cheng (2007)
- Understanding effect of behavioural entropy - eliciting useful personality characteristics from large-scale data.
- Use of high-frequency transaction data (itself a sub-literature of use of newly available large-scale datasets).

2 Methods

2.1 Dataset description

We use data from Money Dashboard (MDB), a financial management app that allows its users to link accounts from different banks to obtain an integrated view of their finances.[3] The dataset contains more than 500 million transactions made between 2012 and June 2020 by about 250,000 users, and provides information such as date, amount, and description about the transaction as well as account and user-level information.

The main advantages of the data for the study of consumer financial behaviour are its high frequency, that it is automatically collected and updated and thus less prone to errors and unaffected by biases that bedevil survey measures, and that it offers a view of consumers' entire financial life across all their accounts, rather than just a view of their accounts held at a single bank, provided they added all their accounts to MDB. The main limitation is the non-representativeness of the sample relative to the population as a whole. Financial management apps are known to be used disproportionally by men, younger people, and people of higher socioeconomic status (Carlin et al. 2019). Also, as pointed out in Gelman et al. (2014), a willingness to share financial information with a third party might not only select on demographic characteristics, but also for an increased need for financial management or a higher degree of financial sophistication. Because our analysis does not rely on representativeness, we do not address this.[4]

Data issues Bourquin et al. (2020) argue that because some of the accounts in the data will be joint accounts, units of observations should be tought of as "households" rather than "users". We do not agree that this is the most prudent approach. The validity of thinking of units as households depends on the proportion of users in the data who add joint accounts and on the proportion of transactions – out of a user's total number of transactions – additionally observed as a result. Given that the sample is skewed towards younger individuals we think it is unlikely that a majority of them has added joint accounts. Furthermore, it seems reasonable to assume that in most cases, joint accounts are mainly used for common household expenditures similar that are similar to those of a single user (albeit in higher amounts), and are thus unlikely to alter the observed spending profile much. Thus, we think of units of observations as individuals, not households.

Some accounts might be business accounts. Using versions of the algorightms used by Bourquin et al. (2020) to identify such accounts showed, however, that such accounts only make up a tiny percentage of overall accounts and would not influence our results.

[3] https://www.moneydashboard.com.

[4] For an example of how re-weighing can be used to mitigate the non-representative issue, see Bourquin et al. (2020).

We thus do not exclude them.

2.2 Preprocessing and sample selection

We restrict our sample to users for whom we can observe a regular income, can be reasonably sure that they have added all their bank account to MDB, and for whom we observe at least six months of data. Table 1 summarises the sample selection steps we applied to a 1 percent sample of the raw data, associated data losses, and the size of our final sample.

Table 1: Sample selection

	Users	User-months	Txns	Txns (m£)
Raw sample	27,175	795,338	65,972,558	12,527
Drop first and last month	26,565	741,170	64,157,932	12,179
At least 6 months of data	23,238	732,499	63,592,713	12,074
At least one savings account	14,315	473,814	43,983,467	8,898
At least one current account	14,028	466,827	43,408,017	8,792
At least £5,000 of annual income	5,335	159,663	16,815,335	3,339
At least 10 txns each month	4,789	142,602	15,328,431	3,023
At least £200 of monthly spend	4,175	122,174	13,592,387	2,713
Complete demographic information	3,417	104,660	11,689,245	2,299
Drop test users	3,410	104,307	11,638,106	2,292
Working age	3,345	102,302	11,465,704	2,241
Final sample	3,345	102,302	11,465,704	2,241

2.3 Dependent variables

Identifying savings transactions: We classify as payments into savings accounts all savings account credits of £5 or more that are not identified as interest payments or automated "save the change" transfers (similarly for debits).[5]

Dummy for savings txn in current month. Motivation: MPS (2018) finds that saving habit is often more important than amount saved.

2.4 Spending profiles

We define a user's spending profile as the distribution of the number of spending transactionas across different spend categories. To summarise these distributions, we calculate spending entropy, based on the formula proposed by Shannon (1948), who defines entropy as $H = -\sum p_i log(p_i)$, which sums, for all possible events, the product of the probability

[5] While standing order transactions are unlikely to be related to entropy in the short-run, we do not exclude such transactions since, best we can tell, the only account for a small fraction of total transactions.

of an event i occuring with the logarithm of that probability.[6] The base the logarithm is often chosen to be 2, though other choices are possible.[7] Entropy is a cornerstone of information theory, where it measures the amount of information contained in an event. In the behavioural sciences, behavioural entropy has recently been shown to predict the frequency of grocery visits and the per-capita spend per visit (Guidotti et al. 2015), the amount of calories consumed (Skatova et al. 2019), and the propensity for financial distress (Muggleton et al. 2020). In our context, we define the entropy of a user's spending profile in a particular period as:[8]

$$H = -\sum_{c \in \mathcal{C}} p_c log(p_c), \tag{1}$$

where $\mathcal{C}$ is the set of all spending categories, p_c the probability that an individual makes a purchase in spending category c, and log the base 2 logarithm. Higher entropy means that transactions are more equal across different spending categories, which makes it hard to predict the next transaction, whereas low entropy profiles have the bulk of transactions in a few dominant categories (such as groceries and transportation) and have relatively few transactions in other categories.[9] For simpler interpretation of our regression coefficients below, we standardise entropy scores to have a mean of 0 and a standard deviation of 1.

We calculate entropy based on three sets of spend categories. The first measure is based on 9 spending categories used by Muggleton et al. (2020).[10] The second measure is based on our own, more fine-grained, categorisation into 48 different categories.[11] The third measure is based on merchant names, as labelled by Money Dashboard.

We also calculate spending category probabilities in two different ways. To calculate what we call "unsmoothed" entropy scores, we calculate the p_cs in Equation 1 as simple frequentist probabilities

$$p_c = \frac{f_c}{F}, \tag{2}$$

where f_c is the number of transactions in spend category c (the frequency with which c occurs) and $F = \sum_{c \in \mathcal{C}} f_c$ the total number of spending transactions. To avoid taking the log of zero for categories with zero transactions, the sum in Equation 1 is taken over categories with positive transaction counts only.[12] To calculate "smoothed" entropy scores,

[6]Shannon entropy is customarily denoted as H following Shannon's own naming after Ludwig Boltzman's 1872 H-theorem in statistical mechanics, to which it is analagous.

[7]The choice of the base for the logarithm varies by application and determines the units. Base 2 means that information is expressed in bits. The natural logarithm, another popular choice, expresses information in *nats*.

[8]We omit individual and time subscripts to keep notation simpler.

[9]For further discussion on how to interpret Equation 1, see Appendix A.

[10]The precise mapping from MDB transaction tags into these 9 categories is available on Github.

[11]The precise mapping from MDB transaction tags into these 48 categories is available on Github.

[12]This is automatically handled by the entropy implementation of Python's SciPy package, which is what we use to calculate entropy scores.

we apply additive smoothing to calculate propabilities as

$$p_c^s = \frac{f_c + 1}{F + |\mathcal{C}|}, \tag{3}$$

where the size of set $\mathcal{C}$, $|\mathcal{C}|$, is the number of unique spending categories. Hence, additive smoothing simply adds one to the numerator and the number of unqiue spending categories to the denominator of the unsmoothed probabilities. Because categories with a zero transaction count will have a numerator of 1, the sum in Equation 1 will be taken over all categories.

One way to think of entropy is as a function of a number of simple components, and we can rewrite Equation 1 in a way that makes this transparent. Let $\mathcal{C}^+ = \{c : f_c > 0\}$ be the set of all spending categories with positive frequency counts (i.e. with at least one transaction) and $\mathcal{C}^0 = \{c : f_c = 0\}$ the set of all spending categories with a zero frequency count. Then, using our definitions of unsmoothed and smoothed probabilities above, we can write unsmoothed entropy as

$$H = -\sum_{c \in \mathcal{C}^+} \left(\frac{f_c}{F}\right) log \left(\frac{f_c}{F}\right), \tag{4}$$

and smoothed entropy as:

$$H^s = -\sum_{c \in \mathcal{C}^+} \left(\frac{f_c + 1}{F + |\mathcal{C}|}\right) log \left(\frac{f_c + 1}{F + |\mathcal{C}|}\right) + |\mathcal{C}^0| \left(\frac{1}{F + |\mathcal{C}|}\right) log \left(\frac{1}{F + |\mathcal{C}|}\right), \tag{5}$$

where the size of set $\mathcal{C}^0$, $|\mathcal{C}^0|$, is the number of all spending categories in which a user makes no transactions in a certain period. These expressions make clear that, by definition, unsmoothed entropy is a function of frequency counts of categories with positive counts only to avoid taking logs of 0, while smoothed entropy has two parts: the additively smoothed unsmoothed entropy, plus a constant term for each spending category with a zero frequency count.

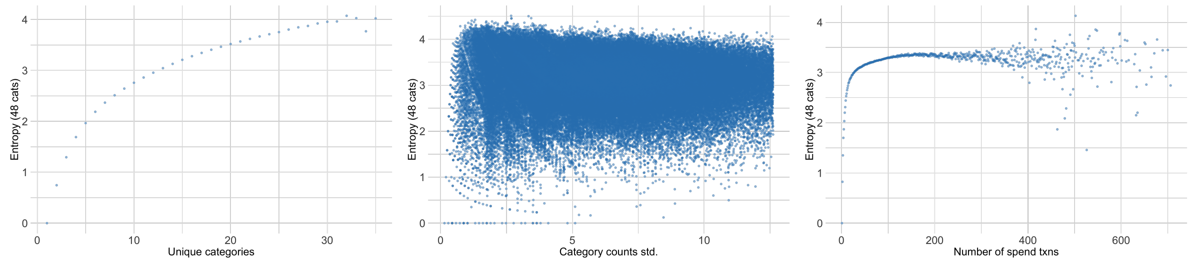
The expressions also make transparent the three main components of both types of entropy: the number of spending categories with a non-zero frequency count (and its complement, the number of categories with a zero frequency count), the variation in the frequency counts of those categories, and the total number of transactions (F).[13]

Figure 1 shows the empirical relationship with our 48-categories-based unsmoothed entropy variable and these three components.[14] We can see that for the values we ob-

[13] The number of total spending categories, $|\mathcal{C}|$, also implicitly determines unsmoothed entropy (since it "scales" the number of categories with a positive frequency count, $|\mathcal{C}^+|$) and explicitly determines smoothed entropy, but it is fixed across users and periods and does not depend on user behaviour.

[14] To highlight the main features of the relationships we have trimmed the component values at the 95th percentile.

Figure 1: Correlation of entropy with its components



Notes: Correlation of 48-categories-based unsmoothed entropy with its three main components: the number of unique spending categories with positive frequency counts (left), the standard deviation of those frequency counts (middle), and the number of total spend transactions (left).

serve in the dataset, entropy increases monotonically in the number of unique spending categories with positive frequency counts, has no clear relationship with the standard deviation of those counts, and increases in the number of total spending transactions up to about 175 transaction, before being increasingly determined by other elements thereafter.

There are a number of alternative ways to characterise spend profiles. We could calculate profiles based on the distribution of transaction values rather than counts. We could also calculate profiles based on inter-temporal rather than intra-temporal distributions, focusing on consistency of purchasing behaviour over time rather than on predictability at any given time (Krumme et al. 2013). Further, we could focus on time-based rather than category-based measures, focusing, for instance, on whether purchases of the same type tend to occur on the same day of the week (Guidotti et al. 2015). Finally, one could also create composite measures based on principal component analysis, an approach used in Eagle et al. (2010). We leave these extensions for future research.

One slight limitation introduced by the imperfect transaction labelling in the MDB data is that entropy scores for high-entropy individuals will be biased downwards. This happens because unlabelled transactions tend to be transactions that are rare (i.e. not grocery or Amazon purchases), and it is high-entropy individuals that are more likely to engage in rare transactions. Because our analysis mainly relies on relative entropy levels, this is not of major consequence and we do not pursue this further.

2.5 Summary statistics

Table 2 provides summary statistics.

Table 2: Summary statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Year income	31.34	44.02	0.43	14.43	22.81	37.05	4,229.21
Income variability	1.23	4.87	0.00	0.21	0.54	1.16	559.67
Has income in month	0.98	0.15	0	1	1	1	1
Has savings	0.48	0.50	0	0	0	1	1
Month spend	2.70	2.65	0.20	1.16	1.91	3.19	17.44
Age	35.14	10.27	18	27	33	42	65
Female	0.39	0.49	0	0	0	1	1
Urban	0.85	0.35	0	1	1	1	1
Unique categories (9)	7.51	1.26	1	7	8	8	9
Unique categories (48)	15.15	4.43	1	12	15	18	35
Unique categories (Merchants)	22.99	9.77	0	16	22	29	85

Notes: Income and spend variables in '000s of Pounds, number of unique categories for spend transaction classification based on 9 categories, 48 categories, and merchant names.

Figure 2

Figure 2: Demographic characteristics of Money Dashboard users

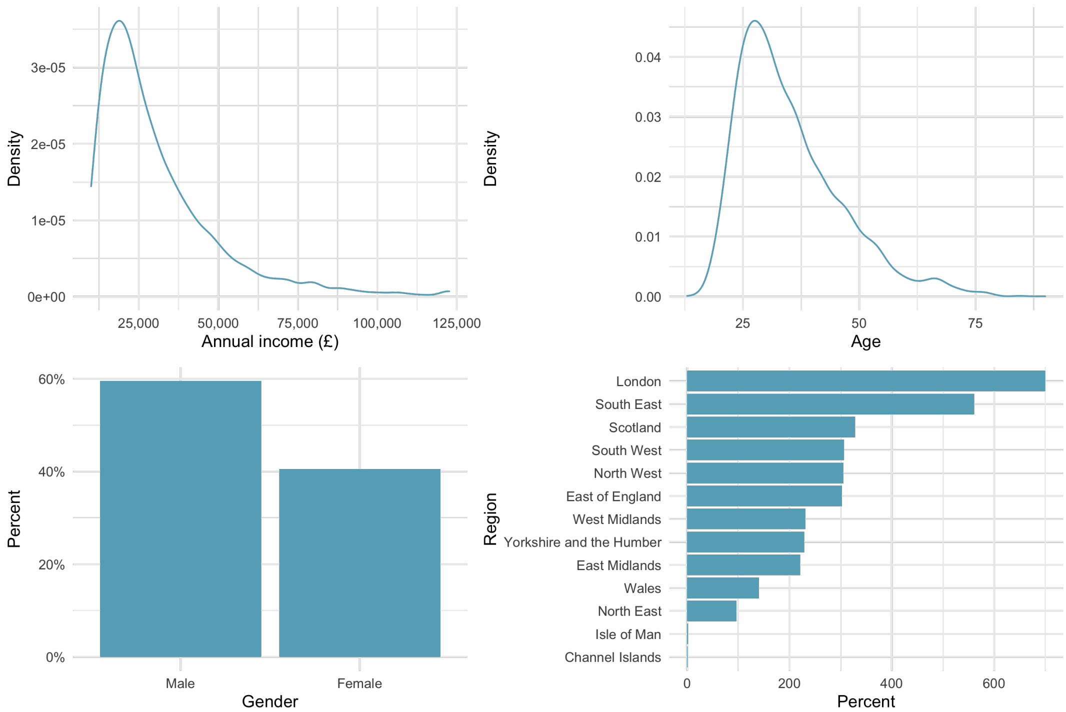
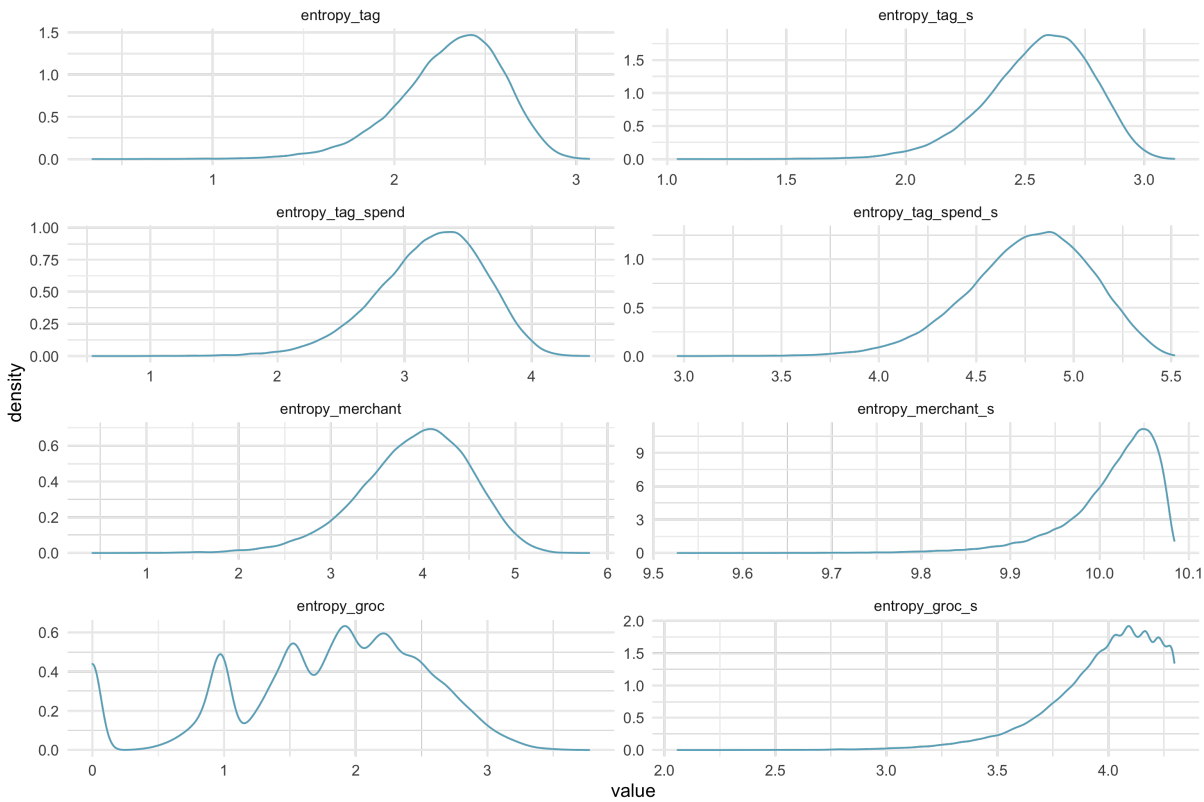


Figure 3

Figure 3: Entropy distributions



Notes:

2.6 Estimation

We estimate models of the form:

$$y_{i,t} = \alpha_i + \lambda_t + \beta H_{i,t} + x'_{i,t}\delta + \epsilon_{i,t}, \tag{6}$$

where $y_{i,t}$ is an indicator variable equal to one if individual i made one or more transfers to any of their savings account in year-month period t and zero otherwise, H_{it} is i's spending entropy in year-month period t, $x_{i,t}$ a vector of control variables, α_i an individual fixed effect, λ_t a year-month fixed effect, and $\epsilon_{i,t}$ the error term.

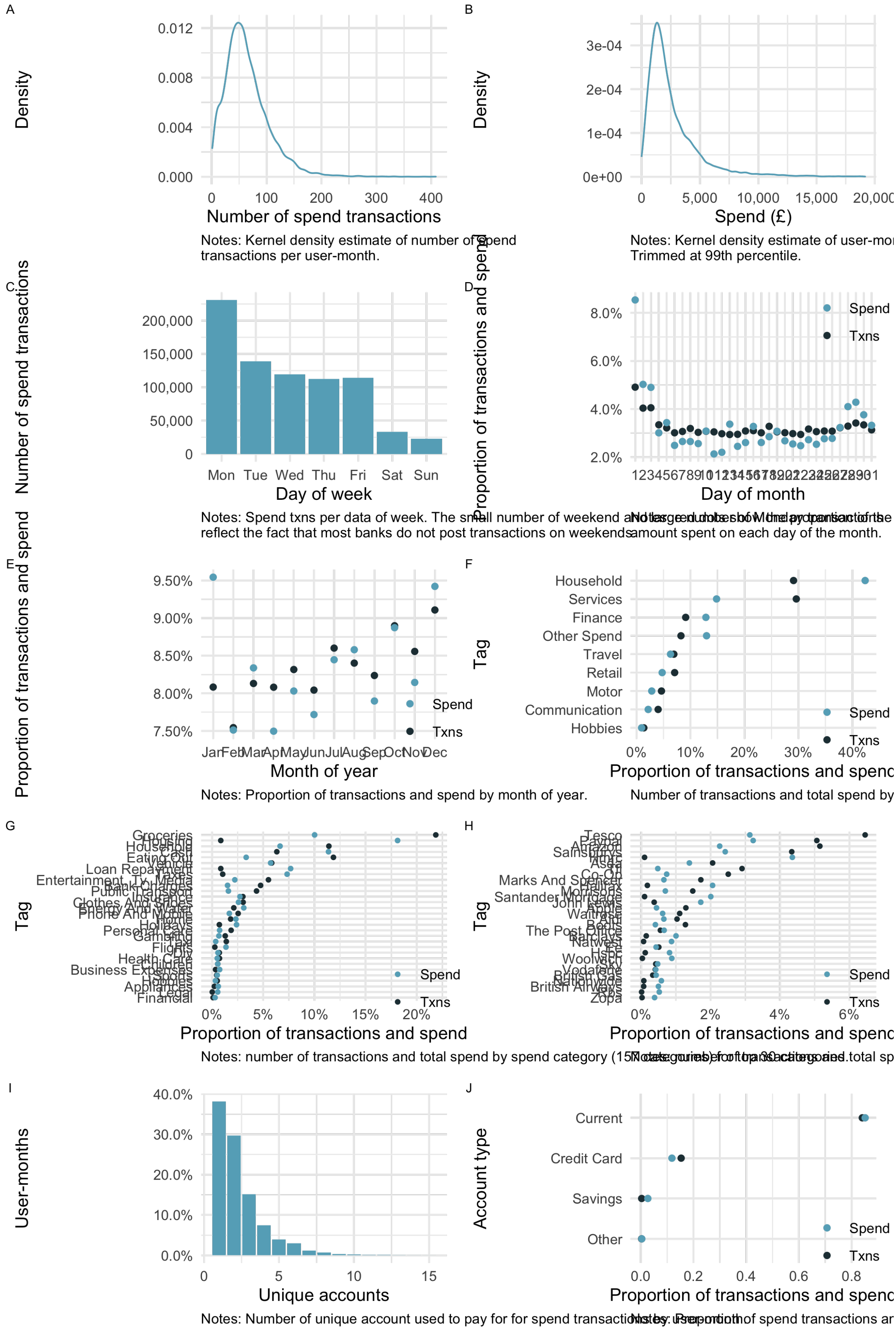
The vector of controls includes month spend, month income, an indicator for whether a user had positive income in a given month, and income variability, calculated as the standard deviation of month income over the previous 12 months.

Note that while we might in principle be worried about reverse causality, since making payments into savings accounts might lead to a non-zero count in an additional spend category and thus change entropy, this is not a concern here. As discussed in Section 2.3 and Section 2.4, we define savings as inflows into savings accounts and define entropy based on the classification of spend transactions on current accounts. If a user pays money from their current into one of their savings account, such a transaction will usually be labelled in their current account as a transfer rather than a spending transaction, and thus not enter the calculation of their entropy score. In Appendix B.1, we provide robustness checks using lagged entropy scores, which produces very similar results.

3 Spending profiles

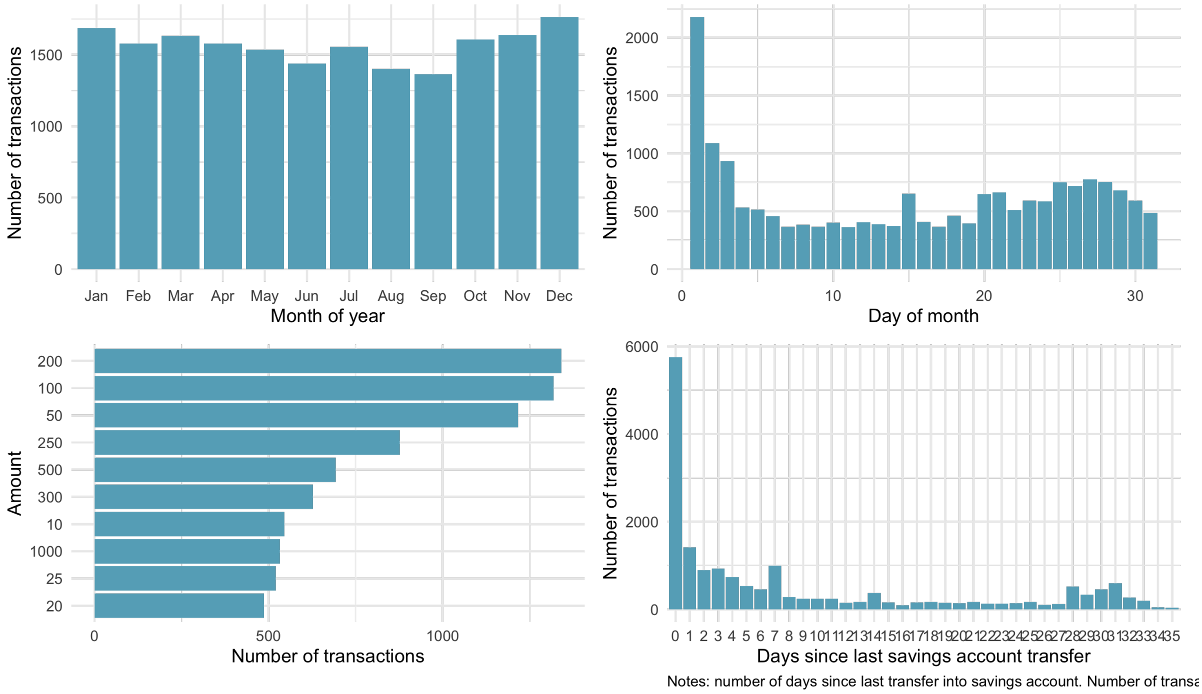
Figure 4

Figure 4: Spending behaviour



4 Savings patterns

Figure 5: Savings behaviour



5 Spending profiles predict emergency savings

Table 3 shows the effect of entropy on the probability of building emergency savings in a given month. Columns (1)-(3) show results for unsmoothed entropy based on 9 categories, 48 categories, and merchant names, respectively. Columns (4)-(6) results for smoothed entropy based on the same variables. All models include user and year-month fixed effects, and standard errors are clustered at the user-level. 95% confidence intervals are shown in brakets.

Results for unsmoothed entropy suggest that a one unit increase in entropy is associated with an increase in the probability of a user making at least one transfer into their savings accounts of between 1.5 and 2.7 percentage points – an effect up to two times larger than that of a £1000 increase in monthly income. Conversely, the effect for unsmooth entropy is smaller in magnitude but runs in the reverse direction: a one-unit increase in the smoothed entropy score is associated with a reduction in the probability of transferring money into savings account of between 0.4 and 1.6 percentage points – an effect that, in absolute magnitude, is about equal to that of a £1000 increase in monthly income.

As discussed in Section 2.6, these results are not a results of reverse causality. While we might think that making a savings transactions might change some or all of the compo-

Table 3: Effect of entropy on P(payment into savings accounts)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Entropy (9 cats)	0.016^{***} [0.013; 0.019]					
Entropy (48 cats)		0.029^{***} [0.025; 0.033]				
Entropy (merchant)			0.032^{***} [0.029; 0.036]			
Entropy (9 cats, smooth)				-0.008^{***} [-0.010; -0.006]		
Entropy (48 cats, smooth)					-0.023^{***} [-0.025; -0.020]	
Entropy (merchant, smooth)						-0.019^{***} [-0.021; -0.016]
Month spend	0.009^{***} [0.009; 0.010]	0.009^{***} [0.008; 0.009]	0.008^{***} [0.008; 0.009]	0.009^{***} [0.009; 0.010]	0.008^{***} [0.007; 0.009]	0.007^{***} [0.007; 0.008]
Month income	0.012^{***} [0.011; 0.013]	0.012^{***} [0.011; 0.013]	0.012^{***} [0.011; 0.013]	0.012^{***} [0.011; 0.013]	0.011^{***} [0.011; 0.012]	0.011^{***} [0.010; 0.012]
Has income in month	0.086^{***} [0.077; 0.094]	0.084^{***} [0.075; 0.092]	0.083^{***} [0.074; 0.091]	0.087^{***} [0.079; 0.096]	0.085^{***} [0.076; 0.093]	0.086^{***} [0.078; 0.095]
Income variability	0.001^{*} [-0.000; 0.001]	0.001^{*} [-0.000; 0.001]	0.001^{*} [-0.000; 0.001]	0.001^{*} [-0.000; 0.001]	0.001^{*} [-0.000; 0.001]	0.000 [-0.000; 0.001]
Fixed-effects						
User	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,043,727	1,043,727	1,043,416	1,043,727	1,043,727	1,043,416
R^2	0.45368	0.45395	0.45410	0.45363	0.45415	0.45410
Within R^2	0.00719	0.00768	0.00807	0.00709	0.00805	0.00808

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

nents of entropy discussed in Section 2.4 – the number of unique spending categories with positive frequency count, the standard deviation of these counts, and the total number of spend transactions – and thus change entropy, this is not the case because of the way we define entropy and savings, and the way spending transactions are categorised. We define entropy based on all current account debits that are identified as spends, while we define savings transactions as the sum of all savings accounts credits. If a user transfers money from their current account to their savings account, this will be identified as a savings transaction, but be identified as a transfer on their current account and thus not considered when calculating their entropy score.

Overall, the effect of entropy in spending profiles is statistically and economically significant, and robust across different definitions. In other words, the scores seem to pick up a feature of the spending distribution that is predictive of savings behaviour.

Two questions remain: first, does entropy capture an element of the spending distributions that is different from what is captured by its three main components? Second, why does smoothing entropy scores flip the direction of the effec? We will address these in turn.

5.1 Is entropy more than the sum of its parts?

In Section 2.4 we show that we can think of both unsmoothed and smoothed entropy as a fundtion of three simple components: the number of unqiue spending categories with a positive frequency count, the standard deviation of those counts, and the number of spending transactions. Here we want to test whether entropy remains predictive of savings behaviour once we control for these components.

Table 4: Controlling for entropy components

Model:	(1)	(2)	(3)	(4)
Variables				
Entropy (48 cats)	0.029***	0.013***		
	[0.025; 0.033]	[0.006; 0.021]		
Entropy (48 cats, smooth)			-0.023***	-0.028***
			[-0.025; -0.020]	[-0.034; -0.022]
Unique categories		0.004***		0.004***
		[0.003; 0.005]		[0.004; 0.005]
Category counts std.		0.002		-0.015***
		[-0.001; 0.006]		[-0.018; -0.011]
Number of spend txns		0.000***		0.001***
		[0.000; 0.001]		[0.001; 0.001]
Month spend	0.009***	0.005***	0.008***	0.005***
	[0.008; 0.009]	[0.004; 0.006]	[0.007; 0.009]	[0.005; 0.006]
Month income	0.012***	0.011***	0.011***	0.011***
	[0.011; 0.013]	[0.010; 0.012]	[0.011; 0.012]	[0.010; 0.012]
Has income in month	0.084***	0.079***	0.085***	0.078***
	[0.075; 0.092]	[0.070; 0.087]	[0.076; 0.093]	[0.070; 0.087]
Income variability	0.001*	0.000	0.001*	0.000
	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]
Fixed-effects				
User	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,043,727	1,043,727	1,043,727	1,043,727
R^2	0.45395	0.45498	0.45415	0.45515
Within R^2	0.00768	0.00956	0.00805	0.00986

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

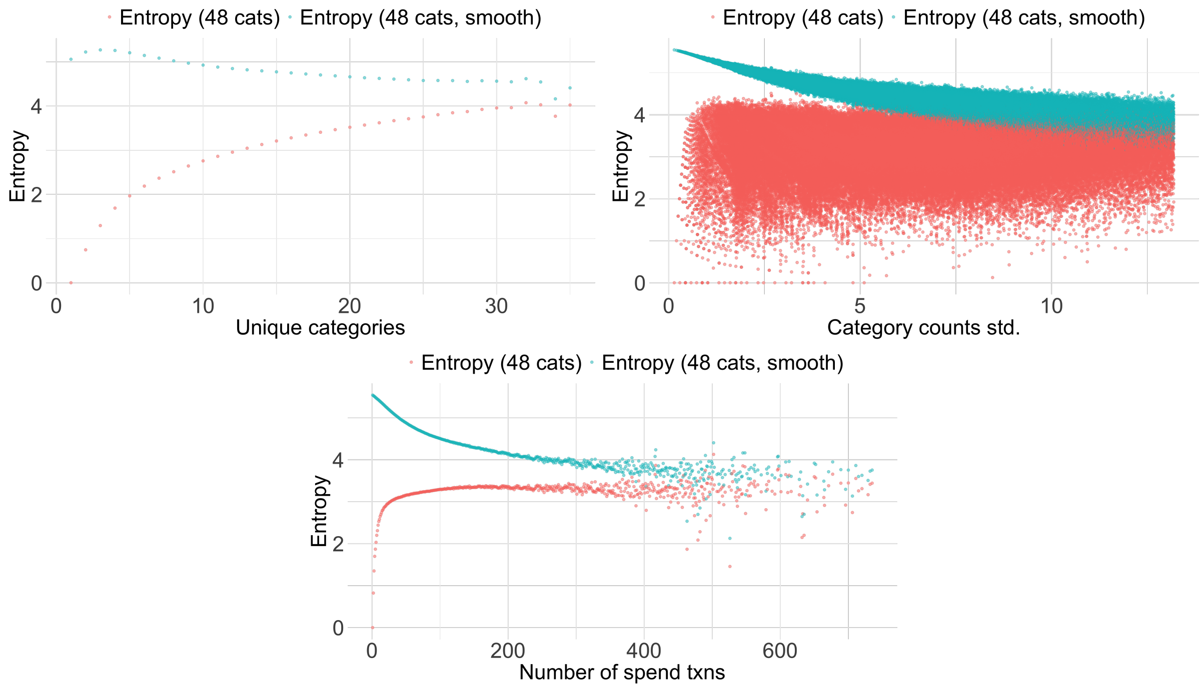
Columns (1) and (3) in Table 4 replicate the results for the 48-category-based unsmoothed and smoothed entropy measures presented in Table 3 for reference. In columns (2) and (4) we additionally control for the three entropy components. Including these components has some effect: for unsmoothed entropy the magnitude of the coefficient is less than half its size and the confidence interval is about twice as wide, while for smoothed entropy the magnitude of the coefficient is a little higher while the width of the confidence interval also roughly doubles. However, both coefficients remain statistically significant and their confidence intervals cover values that are also economically significant. Hence, the results make clear that the results in Table 3 cannot be attributed simply to the effect of one or more of entropy's simple components.

5.2 Why does smoothing flip the direction of the effect

As discussed in Section 2.4, we create smooth entropy measures by applying additive smoothing to the probability that a spending transaction takes place in a given spending category by adding 1 to the transaction count of that spending category in the numerator, and adding the number of spending categories to the total number of spending transactions in the denominator.

While we have just seen above that entropy captures more about users' spending profile, to understand the effect of smoothing on entropy scores it is still instructive to see how it affects scores as a function of the three components. Figure 6 shows unsmoothed and smoothed entropy scores as a function of the number of unique spend categories with positive frequency count (left), the standard deviation of these counts (middle), and the total number of spend transactions (right).

Figure 6: Effect of smoothing on entropy components



Notes: Effect of smoothing on entropy as a function of its three main components: the number of spending categories with positive frequency-counts (left), the standard deviatioin of these counts (middle), and the total number of spending transaction (right). Value ranges for entropy components are trimmed at the 95th percentile.

- Sign reversal is mechanical - Interpret in light of formulas - Suggests that results very fragile to how we define entropy - Also suggests that sign-issue is a red herring

6 Discussion

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A Interpreting entropy

To see how we can interpret entropy as the predictability of a user's spending behaviour, it is useful to have a more complete understanding of Equation 1. The building blocks of entropy is the information content of a single event. The key intuition Shannon (1948) aimed to capture was that learning of the occurrence of a low-probability event is more informative than learning of the occurrence of a high-probability event. The information of an event $I(E)$ is thus inversely proportional to is probability $p(E)$. One way to capture this would be to define the information of event E as $I(E) = \frac{1}{p(E)}$. Yet this implied that an event that is certain to occur had information 1, when it would make sense to have information 0. To remedy this (and also satisfy additional desireable characteristics of an information function), we can use the log of the expression. Hence, the information of event E, often called *Shannon information*, *self-information*, or just *information*, is defined as:

$$I(E) = log\left(\frac{1}{p(E)}\right) = -log(p(E)). \tag{7}$$

Entropy, often called *Information entropy*, *Shannon entropy*, or just *entropy*, is the information of a random variable, X, and captures the expected amount of information of an event drawn at random from the probability distribution of the random variable. It is calcualted as:

$$H(X) = -\sum_{x} p(x) \times log(p(x)) = \sum_{x} p(x)I(x) = \mathbb{E}I(x). \tag{8}$$

For a single event, the key intution was that the less likely an event, the more information is conveyed when it occurs. The related idea for distributions is similar: the less skewed a distribution of a random variable, the less certain the realised value of a single draw from the distribution, the higher is entropy - the maximum entropy distribution is the uniform distribution.

B Additional results

B.1 Endogeneity

As discussed in Section 2.6, one concern one might have about our results in Section 5 is reverse causality: transferring money into savings accounts might change the distribution of spend categories and thus change entropy. As noted previously, this is not a major concern because of the way we calculate savings and spend profiles: savings are calculated as the sum of inflows into savings accounts, while spend profiles are based on the classification of spend transactions in current accounts, and transfers from current to savings accounts are labelled as such and not treated as spend transactions.

However, because transaction labelling is imperfect, it is possible that some transfers are misclassified as spends and included in the calculation of entropy scores. One way to deal with this is to lag entropy scores by one period. Table 5 presents results similar to the main results in the main text, but using entropy lagged by one year-month period as the independent variable of interest. We can see that the results are very similar to thos presented above.

Table 5: Effect of entropy on P(has savings)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Entropy (9 cats)	0.016***					
	[0.013; 0.019]					
Entropy (48 cats)		0.029***				
		[0.025; 0.033]				
Entropy (merchant)			0.032***			
			[0.029; 0.036]			
Entropy (9 cats, smooth)				-0.008***		
				[-0.010; -0.006]		
Entropy (48 cats, smooth)					-0.023***	
					[-0.025; -0.020]	
Entropy (merchant, smooth)						-0.019***
						[-0.021; -0.016]
Month spend	0.009***	0.009***	0.008***	0.009***	0.008***	0.007***
	[0.009; 0.010]	[0.008; 0.009]	[0.008; 0.009]	[0.009; 0.010]	[0.007; 0.009]	[0.007; 0.008]
Month income	0.012***	0.012***	0.012***	0.012***	0.011***	0.011***
	[0.011; 0.013]	[0.011; 0.013]	[0.011; 0.013]	[0.011; 0.013]	[0.011; 0.012]	[0.010; 0.012]
Has income in month	0.086***	0.084***	0.083***	0.087***	0.085***	0.086***
	[0.077; 0.094]	[0.075; 0.092]	[0.074; 0.091]	[0.079; 0.096]	[0.076; 0.093]	[0.078; 0.095]
Income variability	0.001*	0.001*	0.001*	0.001*	0.001*	0.000
	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]	[-0.000; 0.001]
Fixed-effects						
User	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,043,727	1,043,727	1,043,416	1,043,727	1,043,727	1,043,416
R^2	0.45368	0.45395	0.45410	0.45363	0.45415	0.45410
Within R^2	0.00719	0.00768	0.00807	0.00709	0.00805	0.00808

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

B.2 Further results by financial resilience

The Tables below show results presented in Section ?? for alternative entropy variables.

Table 6: Effect of entropy on P(has savings) by income quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income quintile:	1	2	3	4	5
Variables					
Entropy (9 cats)	0.022***	0.006**	0.009***	0.007**	0.006**
	[0.017; 0.026]	[0.001; 0.011]	[0.004; 0.015]	[0.002; 0.013]	[0.000; 0.012]
Month spend	0.011***	0.007***	0.008***	0.007***	0.007***
	[0.010; 0.012]	[0.006; 0.009]	[0.007; 0.009]	[0.006; 0.008]	[0.005; 0.008]
Month income	0.016***	0.011***	0.012***	0.013***	0.008***
	[0.013; 0.019]	[0.004; 0.017]	[0.005; 0.020]	[0.008; 0.019]	[0.007; 0.010]
Income variability	0.000	0.001	0.002***	0.001**	-0.000
	[-0.001; 0.001]	[-0.000; 0.002]	[0.001; 0.004]	[0.000; 0.002]	[-0.001; 0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,462	215,151	208,417	201,319	195,378
R^2	0.59111	0.58937	0.58347	0.58205	0.57151
Within R^2	0.00469	0.00151	0.00193	0.00175	0.00246

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

Table 7: Effect of entropy on P(has savings) by income quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income quintile:	1	2	3	4	5
Variables					
Entropy (9 cats, smooth)	-0.008***	-0.009***	-0.006***	-0.006***	-0.008***
	[-0.012; -0.005]	[-0.012; -0.006]	[-0.009; -0.002]	[-0.009; -0.002]	[-0.012; -0.005]
Month spend	0.011***	0.007***	0.008***	0.007***	0.006***
	[0.010; 0.012]	[0.006; 0.008]	[0.007; 0.009]	[0.006; 0.008]	[0.005; 0.007]
Month income	0.017***	0.011***	0.012***	0.013***	0.008***
	[0.013; 0.020]	[0.004; 0.017]	[0.005; 0.020]	[0.008; 0.019]	[0.007; 0.010]
Income variability	0.000	0.001	0.002***	0.001**	-0.000
	[-0.001; 0.001]	[-0.000; 0.002]	[0.001; 0.004]	[0.000; 0.002]	[-0.001; 0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,462	215,151	208,417	201,319	195,378
R^2	0.59095	0.58944	0.58347	0.58207	0.57158
Within R^2	0.00431	0.00168	0.00193	0.00179	0.00260

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

Table 8: Effect of entropy on P(has savings) by income variability quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income variability quintile:	1	2	3	4	5
Variables					
Entropy (9 cats)	0.011***	0.005*	0.012***	0.016***	0.011***
	[0.006; 0.016]	[-0.001; 0.010]	[0.006; 0.018]	[0.010; 0.022]	[0.006; 0.017]
Month spend	0.008***	0.008***	0.007***	0.007***	0.007***
	[0.007; 0.009]	[0.007; 0.009]	[0.006; 0.008]	[0.006; 0.009]	[0.006; 0.008]
Month income	0.015***	0.010***	0.011***	0.010***	0.010***
	[0.012; 0.017]	[0.008; 0.012]	[0.010; 0.013]	[0.009; 0.012]	[0.009; 0.011]
Has income in month	0.094***	0.077***	0.065***	0.057***	0.068***
	[0.075; 0.113]	[0.057; 0.096]	[0.048; 0.082]	[0.041; 0.072]	[0.054; 0.083]
Income variability	-0.001	0.006**	-0.000	0.001	-0.004***
	[-0.003; 0.002]	[0.001; 0.011]	[-0.004; 0.003]	[-0.001; 0.002]	[-0.007; -0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,462	215,151	208,417	201,319	195,378
R^2	0.61156	0.59945	0.59051	0.59361	0.63509
Within R^2	0.00532	0.00383	0.00456	0.00534	0.00753

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

Table 9: Effect of entropy on P(has savings) by income variability quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income variability quintile:	1	2	3	4	5
Variables					
Entropy (9 cats, smooth)	-0.007***	-0.009***	-0.005***	-0.007***	-0.010***
	[-0.011; -0.004]	[-0.013; -0.006]	[-0.009; -0.002]	[-0.010; -0.003]	[-0.014; -0.007]
Month spend	0.008***	0.008***	0.007***	0.007***	0.007***
	[0.007; 0.009]	[0.007; 0.009]	[0.006; 0.008]	[0.006; 0.009]	[0.006; 0.008]
Month income	0.015***	0.010***	0.012***	0.011***	0.010***
	[0.012; 0.018]	[0.008; 0.012]	[0.010; 0.013]	[0.009; 0.012]	[0.009; 0.011]
Has income in month	0.095***	0.077***	0.066***	0.058***	0.069***
	[0.076; 0.115]	[0.057; 0.096]	[0.049; 0.083]	[0.042; 0.073]	[0.055; 0.083]
Income variability	-0.001	0.006**	-0.000	0.000	-0.004**
	[-0.003; 0.001]	[0.001; 0.011]	[-0.004; 0.003]	[-0.001; 0.002]	[-0.007; -0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,462	215,151	208,417	201,319	195,378
R^2	0.61156	0.59954	0.59048	0.59355	0.63514
Within R^2	0.00533	0.00404	0.00448	0.00519	0.00767

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

Table 10: Effect of entropy on P(has savings) by income quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income quintile:	1	2	3	4	5
Variables					
Entropy (merchant)	0.032***	0.027***	0.024***	0.017***	0.021***
	[0.027; 0.037]	[0.022; 0.033]	[0.019; 0.030]	[0.011; 0.023]	[0.015; 0.027]
Month spend	0.010***	0.006***	0.007***	0.007***	0.006***
	[0.009; 0.011]	[0.005; 0.008]	[0.006; 0.008]	[0.006; 0.008]	[0.005; 0.007]
Month income	0.015***	0.010***	0.012***	0.013***	0.008***
	[0.012; 0.019]	[0.004; 0.017]	[0.005; 0.019]	[0.008; 0.019]	[0.007; 0.010]
Income variability	-0.000	0.001	0.002***	0.001**	-0.000
	[-0.001; 0.001]	[-0.000; 0.002]	[0.001; 0.004]	[0.000; 0.002]	[-0.001; 0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,357	215,087	208,364	201,280	195,328
R^2	0.59137	0.58963	0.58366	0.58211	0.57163
Within R^2	0.00544	0.00229	0.00245	0.00198	0.00288

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

Table 11: Effect of entropy on P(has savings) by income quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income quintile:	1	2	3	4	5
Variables					
Entropy (merchant, smooth)	-0.025***	-0.017***	-0.014***	-0.013***	-0.015***
	[-0.029; -0.022]	[-0.021; -0.013]	[-0.018; -0.011]	[-0.018; -0.009]	[-0.019; -0.012]
Month spend	0.009***	0.006***	0.007***	0.006***	0.005***
	[0.008; 0.010]	[0.005; 0.007]	[0.005; 0.008]	[0.005; 0.007]	[0.004; 0.006]
Month income	0.015***	0.010***	0.011***	0.013***	0.008***
	[0.012; 0.019]	[0.003; 0.017]	[0.004; 0.018]	[0.007; 0.019]	[0.007; 0.010]
Income variability	-0.000	0.001	0.002***	0.001**	-0.000
	[-0.001; 0.001]	[-0.000; 0.002]	[0.001; 0.004]	[0.000; 0.002]	[-0.001; 0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,357	215,087	208,364	201,280	195,328
R^2	0.59153	0.58963	0.58368	0.58225	0.57180
Within R^2	0.00581	0.00230	0.00249	0.00232	0.00327

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

Table 12: Effect of entropy on P(has savings) by income variability quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income variability quintile:	1	2	3	4	5
Variables					
Entropy (merchant)	0.025***	0.020***	0.025***	0.036***	0.026***
	[0.020; 0.031]	[0.014; 0.025]	[0.019; 0.031]	[0.030; 0.042]	[0.020; 0.031]
Month spend	0.007***	0.008***	0.007***	0.006***	0.007***
	[0.006; 0.009]	[0.006; 0.009]	[0.005; 0.008]	[0.005; 0.007]	[0.005; 0.008]
Month income	0.014***	0.010***	0.011***	0.010***	0.010***
	[0.011; 0.017]	[0.008; 0.012]	[0.010; 0.013]	[0.009; 0.012]	[0.009; 0.011]
Has income in month	0.091***	0.075***	0.063***	0.054***	0.066***
	[0.072; 0.111]	[0.055; 0.094]	[0.046; 0.080]	[0.039; 0.069]	[0.052; 0.080]
Income variability	-0.001	0.006**	-0.000	0.000	-0.004**
	[-0.003; 0.001]	[0.001; 0.010]	[-0.004; 0.003]	[-0.001; 0.002]	[-0.007; -0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,369	215,092	208,349	201,276	195,330
R^2	0.61172	0.59956	0.59064	0.59404	0.63529
Within R^2	0.00592	0.00422	0.00506	0.00644	0.00814

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

Table 13: Effect of entropy on P(has savings) by income variability quintile

Model:	(1)	(2)	(3)	(4)	(5)
Income variability quintile:	1	2	3	4	5
Variables					
Entropy (merchant, smooth)	-0.018***	-0.018***	-0.016***	-0.017***	-0.016***
	[-0.021; -0.014]	[-0.022; -0.014]	[-0.019; -0.012]	[-0.020; -0.013]	[-0.021; -0.012]
Month spend	0.007***	0.006***	0.006***	0.006***	0.006***
	[0.006; 0.008]	[0.005; 0.008]	[0.005; 0.007]	[0.005; 0.007]	[0.005; 0.007]
Month income	0.014***	0.010***	0.011***	0.010***	0.010***
	[0.011; 0.017]	[0.007; 0.012]	[0.009; 0.013]	[0.009; 0.011]	[0.009; 0.011]
Has income in month	0.094***	0.075***	0.065***	0.057***	0.068***
	[0.075; 0.113]	[0.056; 0.095]	[0.048; 0.082]	[0.042; 0.072]	[0.054; 0.082]
Income variability	-0.001	0.005**	-0.000	0.000	-0.004**
	[-0.003; 0.001]	[0.000; 0.010]	[-0.004; 0.003]	[-0.001; 0.002]	[-0.006; -0.001]
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	223,369	215,092	208,349	201,276	195,330
R^2	0.61177	0.59980	0.59070	0.59387	0.63537
Within R^2	0.00607	0.00480	0.00520	0.00602	0.00836

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