Spending profiles predict savings*

Fabian Gunzinger Neil Stewart

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1 Introduction

This paper documents variation in spending profiles of a large set of users of a financial management app and shows that spending profiles are related to how much users save and spend.

We can think of total savings as the sum of long-term and short-term savings. Long-term savings are savings for retirement, either individually or through an employer-linked pension scheme. These kinds of savings, and especially savings through pension schemes, are well researched. In contrast, there is almost no research on short-term savings, which comprise savings for particular goals such as a new car, a holiday, or a wedding, and emergency savings to have a buffer for unexpected events. (See nest2021supporting for more on emergency savings) We aim to close this gap. In our data, we cannot distinguish between goal-oriented and emergency savings, so we focus on total short-term savings[1]

Studying the determinants of"emergency savings" is important because even though around a quarter of adults in the UK and the US are unable to cover irregular expenses like car and medical bills,[2] there is little research that studies why people have low levels of "emergency savings" and test ways to help them build such savings.[3]

Studying spending profiles are 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 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).

[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] 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).

[3] In contrast, there is a large body of research on pension savigns. Well-documented behavioural biases that help explain undersaving 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.

Contribution:

- Systematically documenting "emergency savings" patterns.
- Systematically documenting variation in spending profiles.
- Showing that within-user irregularity in spending profiles is associated with lower "emergency savings" and higher "discretionary spending".

Literature:

- Main 1: Understanding emergency savings behaivour (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.
- Main 2: Understanding effect of behavioural entropy - eliciting useful personality characteristics from large-scale data
- Also 2: Use of high-frequency transaction data (itself a sub-literature of use of newly available large-scale datasets)

Structure of paper:

- Part I: describtive states of how and when people spend and save
- Part II: define measures that characterise spend profile
- Part III: regression analysis

Literature:

- Savings lit: Lunt and Livingstone (1991) and Oaten and Cheng (2007)

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.[4] 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

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

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.[5]

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. 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.

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

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).[6]

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.[7] To summarise these distributions, we calculate spending entropy, based on the formula proposed by Shannon (1948), which defines entropy as:[8]

$$H = -\sum p_i log(p_i), \tag{1}$$

where p_i is the probability that an individual makes a purchase in spending category i, and log is the base 2 logarithm.[9]

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

[6]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.

[7]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.

[8]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.

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

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 the context of spending profiles, 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.[10]

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).[11] The second measure is based on our own, more fine-grained, categorisation into 48 different categories.[12] The third measure is based on merchant names, as labelled by Money Dashboard.

We also handle categories with zero transaction counts in two different ways. To calculate what we call "unsmoothed" entropy scores, we calculate the p_is in Equation 1 as simple frequentist probabilities

$$p_i^{us} = \frac{T_i}{\sum_{i=1}^{N} Ti}, \tag{2}$$

where T_i is the number of transactions in spend category i and N the number of categories. 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.[13] To calculate "smoothed" entropy scores, we apply additive smoothing to calculate propabilities as

$$p_i^{s} = \frac{T_i + 1}{\sum_{i=1}^{N} Ti + N}. \tag{3}$$

Because categories with a zero transaction count will have a numerator of 1, the sum in Equation 1 will be taken over all categories.

The imperfect transaction labelling in the MDB data creates a downward bias in entropy scores for high-entropy individuals. 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.

2.5 Summary statistics

Table 2 provides summary statistics.

Figure 1

[10] For further discussion on how to interpret Equation 1, see Appendix **??**.

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

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

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

Table 2: Summary statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
user_id	476,918.200	59,724.570	361,990	426,510	474,750	527,090	589,670
ym	584.110	11.502	555	575	584	593	607
ymn	201,828.900	99.377	201,604	201,712	201,809	201,906	202,008
txns_count	117.829	77.199	1	70	102	145	1,522
txns_volume	24,486.070	95,626.350	202.890	6,008.070	10,672.090	20,875.490	8,973,596.000
month_income	3,210.120	2,642.140	420.343	1,556.612	2,364.224	3,966.723	15,388.180
inflows	852.165	2,875.060	0.000	0.000	0.000	410.000	21,958.480
outflows	850.291	2,781.575	0.000	0.000	0.000	400.000	20,466.230
netflows	−13.629	2,018.053	−10,805.000	0.000	0.000	64.000	10,600.000
netflows_norm	−0.007	0.714	−3.813	0.000	0.000	0.025	3.607
inflows_norm	0.317	0.983	0.000	0.000	0.000	0.181	7.280
outflows_norm	0.328	1.024	0.000	0.000	0.000	0.175	7.595
has_pos_netflows	0.293	0.455	0	0	0	1	1
pos_netflows_norm	0.275	5.083	0.000	0.000	0.000	0.025	712.569
t	0.436	0.496	0	0	0	1	1
tt	−1.981	13.079	−37	−10	−2	6	44
month_spend	3,028.719	3,137.228	200.000	1,267.230	2,102.130	3,538.840	20,442.220
age	37.453	10.817	19	29	35	44	85
is_female	0.398	0.490	0	0	0	1	1
is_urban	0.852	0.355	0	1	1	1	1
has_sa_account	1.000	0.000	1	1	1	1	1
generation_code	2.542	0.684	0	2	3	3	4
new_loan	0.028	0.166	0	0	0	0	1
unemp_benefits	0.000	0.000	0	0	0	0	0
pct_credit	9.959	19.749	0.000	0.000	0.000	9.555	100.000

Figure 1: Demographic characteristics of Money Dashboard users

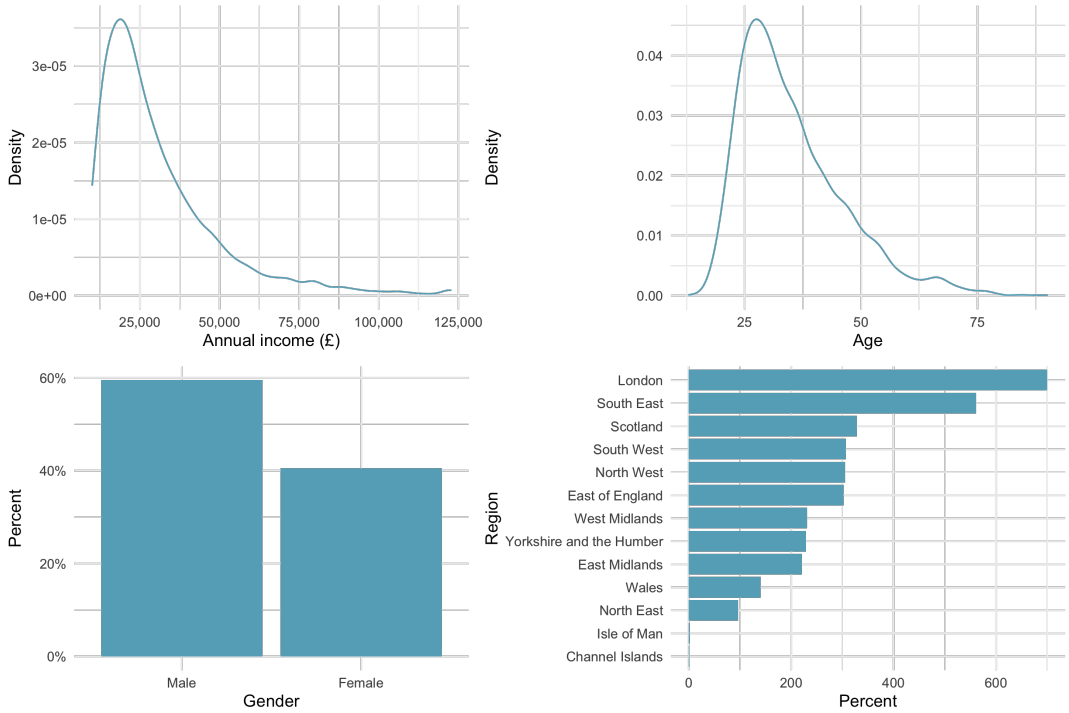
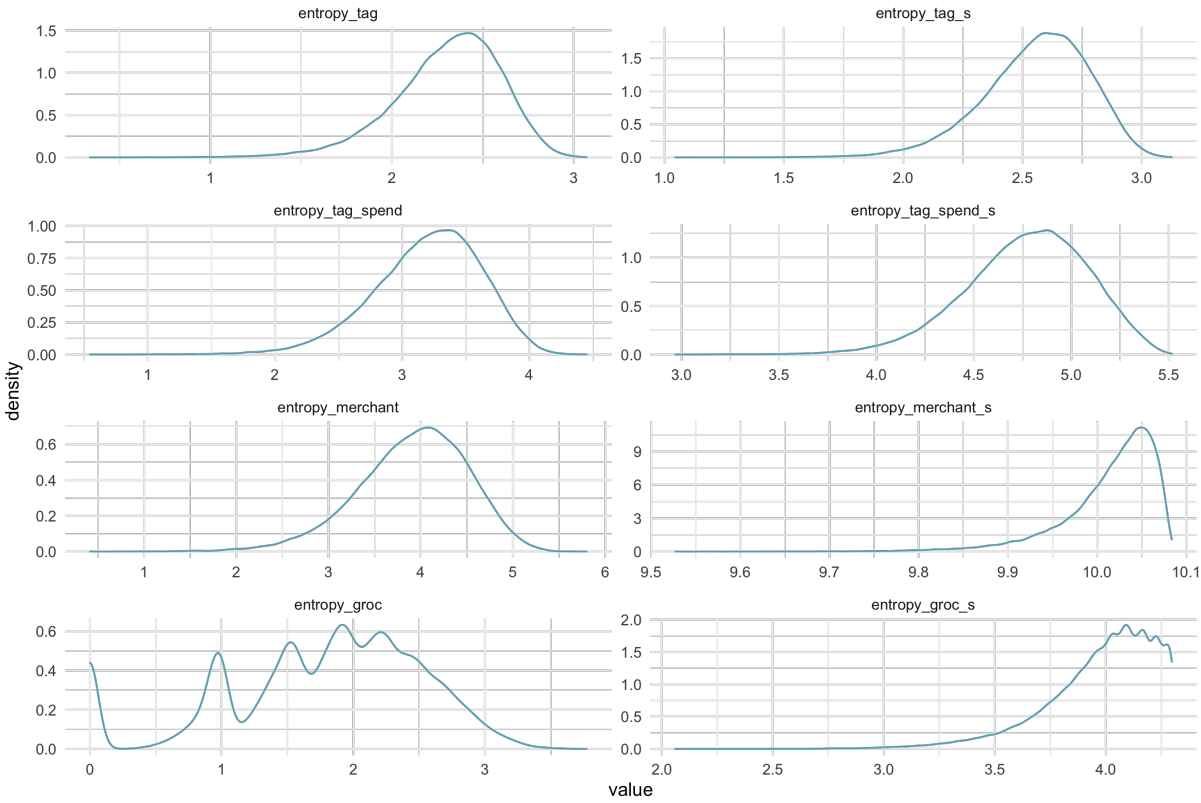


Figure 2

Figure 2: Entropy distributions



Notes:

2.6 Model specification

We estimate models of the form:

$$y_{i,t} = \alpha_i + \lambda_t + \beta H_{i,t} + x'_{i,t}\delta + \epsilon_{i,t}, \tag{4}$$

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.

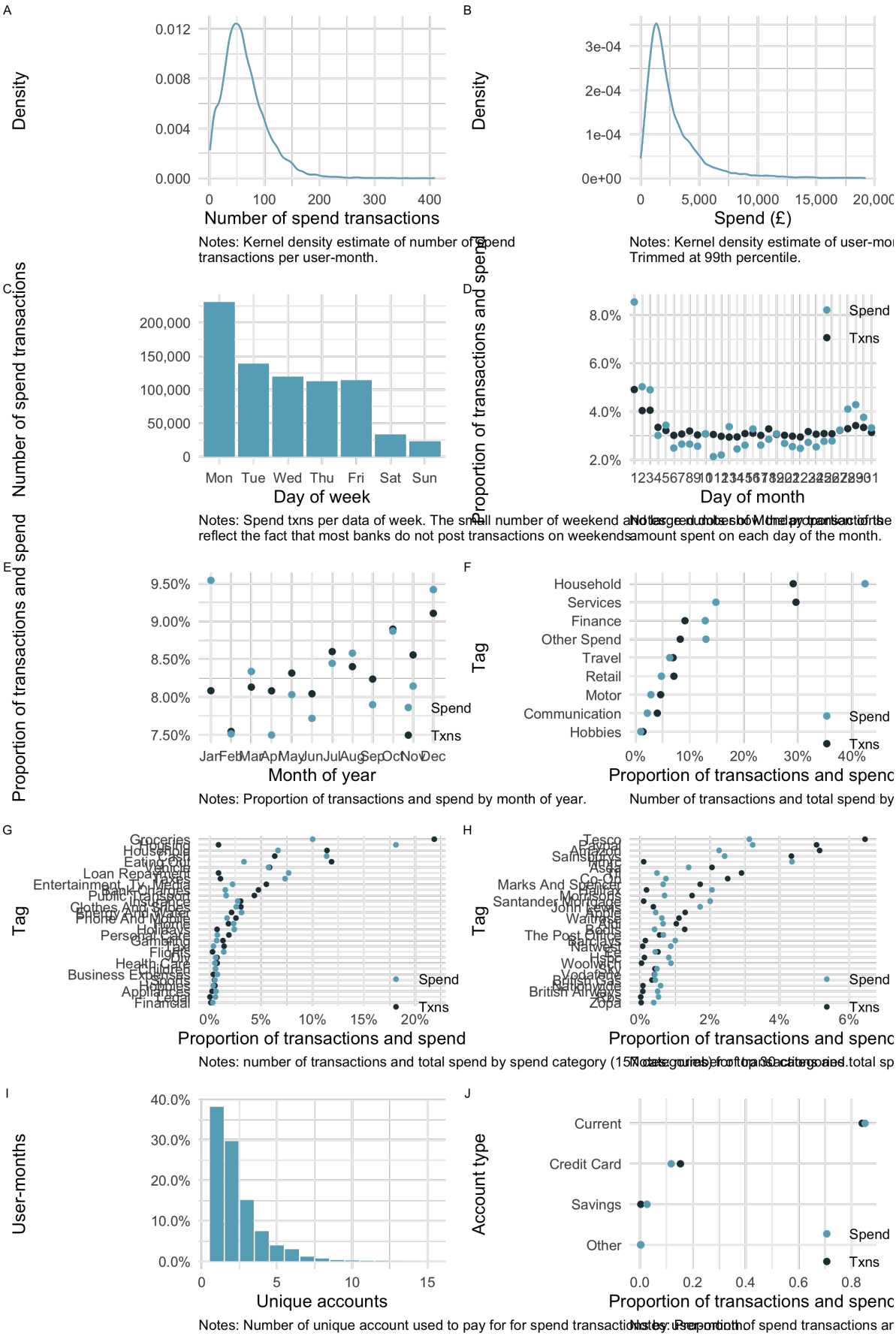
Note that while we might in principle be worried about reverse causality, since making payments into savings accounts might lead to a non-zero count in an additional spend category and thus change entropy, this is not a concern here. As discussed in Section 2.3 and Section 2.4, we define savings as inflows 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, this will usually be labelled in their current account as a transfer and not enter the calculation of their entropy score. In Appendix B, we provide robustness checks using lagged entropy scores and controlling for the number of non-zero categories, which broadly leave

the results unchanged.

3 Spending profiles

Figure 3

Figure 3: Spending behaviour



Notes: Kernel density estimate of number of spend transactions per user-month.

Notes: Kernel density estimate of user-mo
Trimmed at 99th percentile.

Notes: Spend txns per data of week. The small number of weekend and
reflect the fact that most banks do not post transactions on weekends

Notes: Proportion of transactions and spend by month of year.

Number of transactions and total spend by

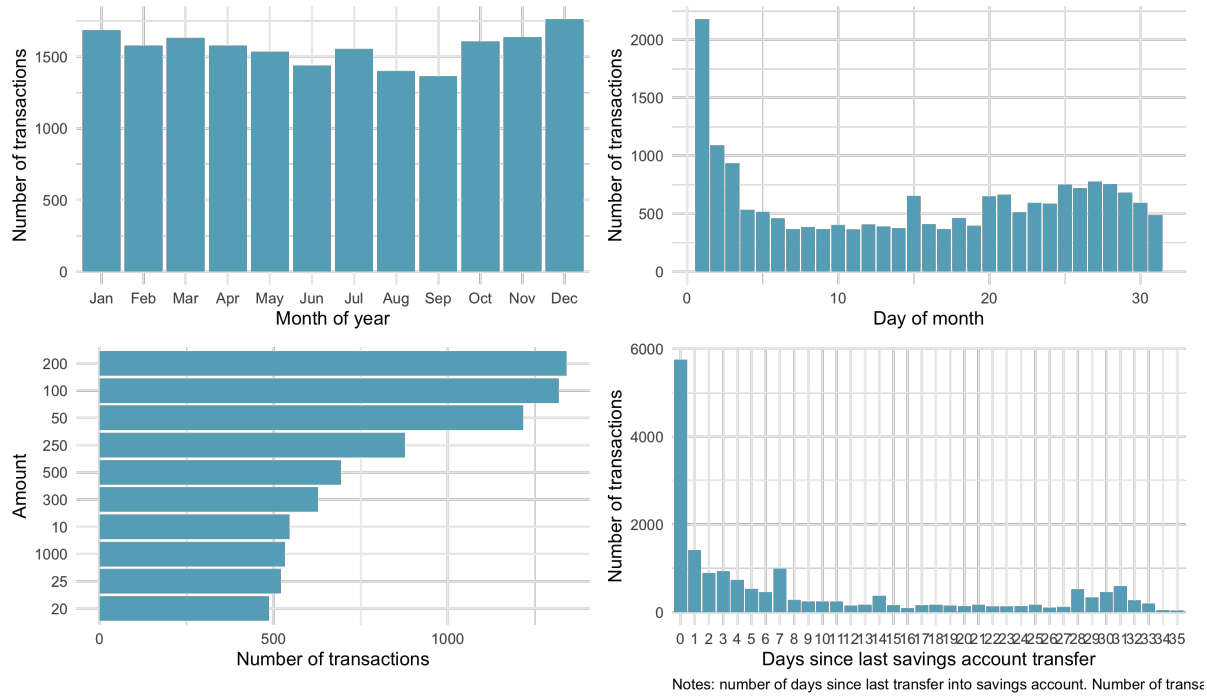
Notes: number of transactions and total spend by spend category (15 categories) for top 30 categories.

Notes: Number of unique account used to pay for for spend transactions by

Notes: Proportion of spend transactions ar

4 Savings patterns

Figure 4: Savings behaviour



5 Spending profiles predict emergency savings

Table 3 shows the effect of entropy on the probability of having emergency savings. 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. 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.

Overall, then, 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.

But how can we account for the opposite sign for smoothed and unsmoothed entropy scores? We don't have the answer to this yet...

Table 3: Effect of entropy on P(transfer 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***	0.008***	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*

6 Discussion

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A Understanding 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:

$$I(E) = log\left(\frac{1}{p(E)}\right) = -log(p(E)). \tag{5}$$

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:

$$H(X) = -\sum_x p(x) \times log(p(x)) = \sum_x p(x)I(x) = \mathbb{E}I(x). \tag{6}$$

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 Robustness

As discussed in Section **??**, one concern one might have about our results in Section **??** 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. Two ways to deal with this is to use lagged entropy scores and to explicitly control for the number of non-zero spend categories used to calculate entropy scores. Here, we show that our results remain qualitatively unchanged with both of these approaches.

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, while Table 4 adds the number

of non-zero spend categories as an additional control.

Table 4: Effect of entropy on P(has savings account inflows)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Entropy lag (9 cats)	0.009*** [0.006; 0.012]					
Entropy lag (48 cats)		0.013*** [0.010; 0.016]				
Entropy lag (merchant)			0.013*** [0.010; 0.016]			
Entropy lag (9 cats, smooth)				-0.004*** [-0.006; -0.002]		
Entropy lag (48 cats, smooth)					-0.010*** [-0.013; -0.008]	
Entropy lag (merchant, smooth)						-0.008*** [-0.011; -0.006]
Month spend	0.008*** [0.008; 0.009]	0.007*** [0.006; 0.007]	0.007*** [0.006; 0.007]	0.008*** [0.008; 0.009]	0.006*** [0.006; 0.007]	0.006*** [0.005; 0.007]
Month income	0.012*** [0.011; 0.013]	0.011*** [0.010; 0.012]	0.011*** [0.010; 0.012]	0.012*** [0.011; 0.013]	0.011*** [0.010; 0.012]	0.011*** [0.010; 0.012]
Has income in month	0.078*** [0.069; 0.087]	0.075*** [0.067; 0.084]	0.077*** [0.068; 0.086]	0.078*** [0.070; 0.087]	0.076*** [0.067; 0.085]	0.078*** [0.069; 0.087]
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]	0.001* [-0.000; 0.001]
Unique categories	0.014*** [0.012; 0.015]	0.006*** [0.006; 0.007]	0.003*** [0.003; 0.003]	0.015*** [0.013; 0.016]	0.006*** [0.006; 0.007]	0.003*** [0.003; 0.003]
Fixed-effects						
User id	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,009,843	1,009,843	1,009,554	1,009,843	1,009,843	1,009,554
R^2	0.45840	0.45888	0.45884	0.45838	0.45892	0.45888
Within R^2	0.00791	0.00878	0.00885	0.00787	0.00887	0.00891

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

Table 5: Effect of entropy on P(transfer into savings accounts)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Entropy lag (9 cats)	0.015*** [0.012; 0.019]					
Entropy lag (48 cats)		0.024*** [0.021; 0.028]				
Entropy lag (merchant)			0.027*** [0.023; 0.030]			
Entropy lag (9 cats, smooth)				-0.004*** [-0.006; -0.002]		
Entropy lag (48 cats, smooth)					-0.016*** [-0.018; -0.013]	
Entropy lag (merchant, smooth)						-0.013*** [-0.016; -0.011]
Month spend	0.009*** [0.009; 0.010]	0.009*** [0.008; 0.010]	0.009*** [0.008; 0.010]	0.009*** [0.009; 0.010]	0.009*** [0.008; 0.009]	0.008*** [0.008; 0.009]
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]	0.012*** [0.011; 0.013]	0.011*** [0.010; 0.012]
Has income in month	0.083*** [0.074; 0.092]	0.082*** [0.073; 0.091]	0.082*** [0.073; 0.091]	0.084*** [0.075; 0.093]	0.083*** [0.074; 0.092]	0.084*** [0.075; 0.092]
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]	0.001* [-0.000; 0.001]
Fixed-effects						
User id	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,009,843	1,009,843	1,009,554	1,009,843	1,009,843	1,009,554
R^2	0.45785	0.45802	0.45809	0.45775	0.45803	0.45800
Within R^2	0.00691	0.00722	0.00748	0.00671	0.00724	0.00731

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