# Entropy*

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## 1 Introduction

We use the following nomenclature throughout:

**user** individual

**tag** spending category

## 2 Data

### 2.1 Dataset description

Data is provided by Money Dashboard (MDB), a UK-based financial management app that allows its users to add accounts from all their banks to obtain an integrated view of their finances. Our dataset contains information on more than 500 million transactions made between 2012 and June 2020 by more than 250,000 users. For each transaction, we can see the amount, date, and description of the transaction, as well as transaction *tags*, classifications added by MDB

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that indicate the type of the transaction (e.g. 'groceries', 'insurance'). We also have basic information on each user (e.g. year of birth, postcode sector) as well information about each bank account (e.g. type of account, date added).

The main advantages of the data for the study of consumer financial behaviour are its high (transaction-level) 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, MAS 2014). 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, one could argue, for a higher degree of financial sophistication. However, while non-representativeness could partially be addressed by re-weighting the sample, as was done in Bourquin et al. (2020), it is not of much consequence for our purpose here, since our ability to infer behaviour traits from transaction data is not dependent on having a representative sample of people.

Further limitations:

- To the extent that users link shared accounts, they might be more appropriately thought of as households rather than individual usres (Bourquin et al. 2020). We assume that in the majority of cases, shared partner accounts are used for shared household expenses rather than personal expenses, and that salary payments are paid into personal accounts. To the extent that this is true, identified salaries are to a single individual, and expenses made by a partner with a shared account would mainly be for household items that an individual would have also purchased if they lived on their own (albeit in smaller quantities), but not for additional spending categories, which would impact our entropy spending tag based entropy measure.

- 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

The MDB data is noisy. We perform a number of preprocessign steps to deal with that.

- Duplicates handling.

- We trim all variables at the 1-percent level on the upper end of the distribution for variables that take non-negative values only and on both ends of the distribution for all other variables. We trim (replace outliers with missing values) rather than winsorise (replace outliers with the cutoff percentile value) because we believe that outliers result from errors in the data rather than represent genuine information.

- Actually, we don't do either of the above. With the harsher selection methods, the statistics are very reasonable, which, if anything, would suggest using winsorizing. However, [this](https://blogs.sas.com/content/iml/2017/02/08/winsorization-good-bad-and-ugly.html) article convincingly argues that we shouldn't do that in our case.

Table 1: Sample selection

| | Users | Accounts | Transactions | Value (£M) |
|---|---|---|---|---|
| Raw sample | 23,804 | 122,288 | 58,440,234 | 11,014.2 |
| One or more current and savings account | 14,327 | 94,576 | 41,158,865 | 8,322.8 |
| At least 6 months of data | 13,313 | 91,147 | 40,935,887 | 8,280.8 |
| No gaps in observed months | 11,869 | 79,958 | 36,296,994 | 7,355.8 |
| Monthly debits of at least £200 | 7,058 | 43,591 | 22,685,516 | 4,450.5 |
| Income in 2/3 of all observed months | 6,058 | 38,326 | 20,265,718 | 3,998.9 |
| Yearly income of at least £10k | 3,698 | 22,087 | 11,835,905 | 2,130.6 |
| Demographic information available | 3,103 | 18,571 | 10,318,607 | 1,837.2 |
| Final sample | 3,103 | 18,571 | 10,318,607 | 1,837.2 |

### 2.3 Summary statistics

The four panels in Figure 1 provide an overview of demographic characteristics of our sample. It makes clear that Money Dashboard users are not a representative sample of the UK population: they are predominantly males in their thirties who live in London or the South East and are relatively well off (the income distribution is shifted to the right relative to the UK as a whole).[1]

[1]To calculate incomes, we broadly follow Hacioglu et al. (2020) in defining total income as the sum of earnings, pension income, benefits, and other income.

Figure 1: Demographic characteristics of Money Dashboard users

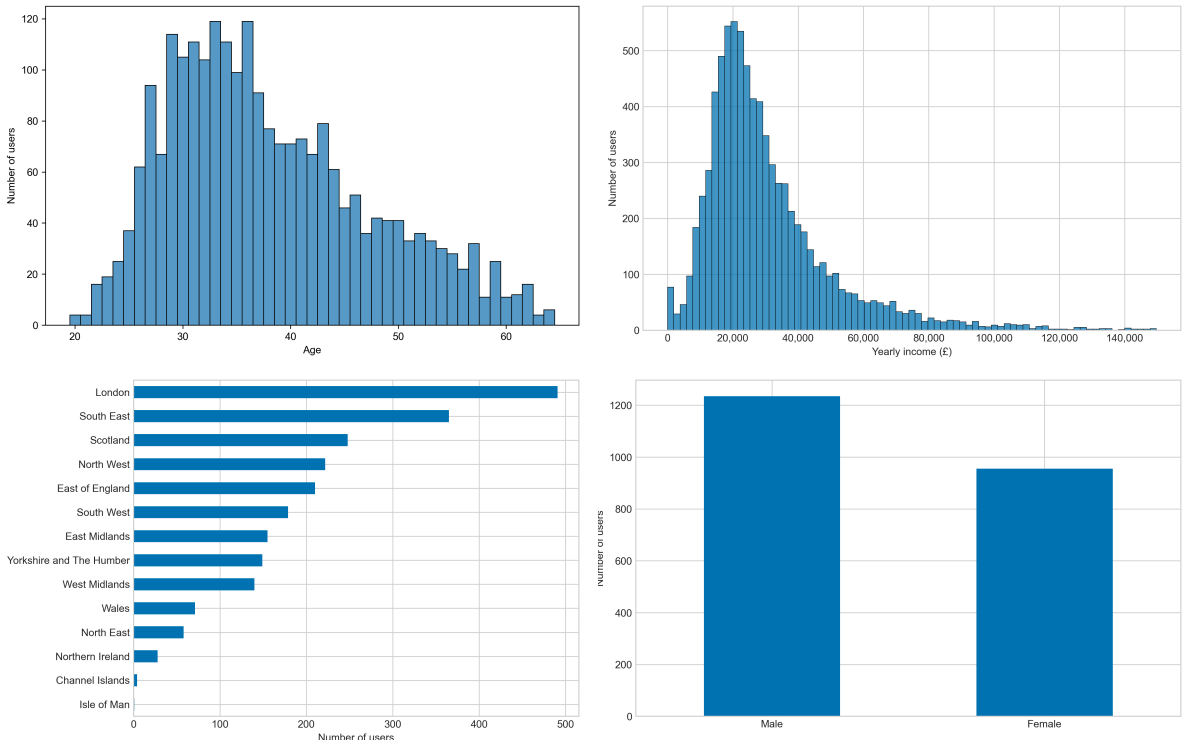
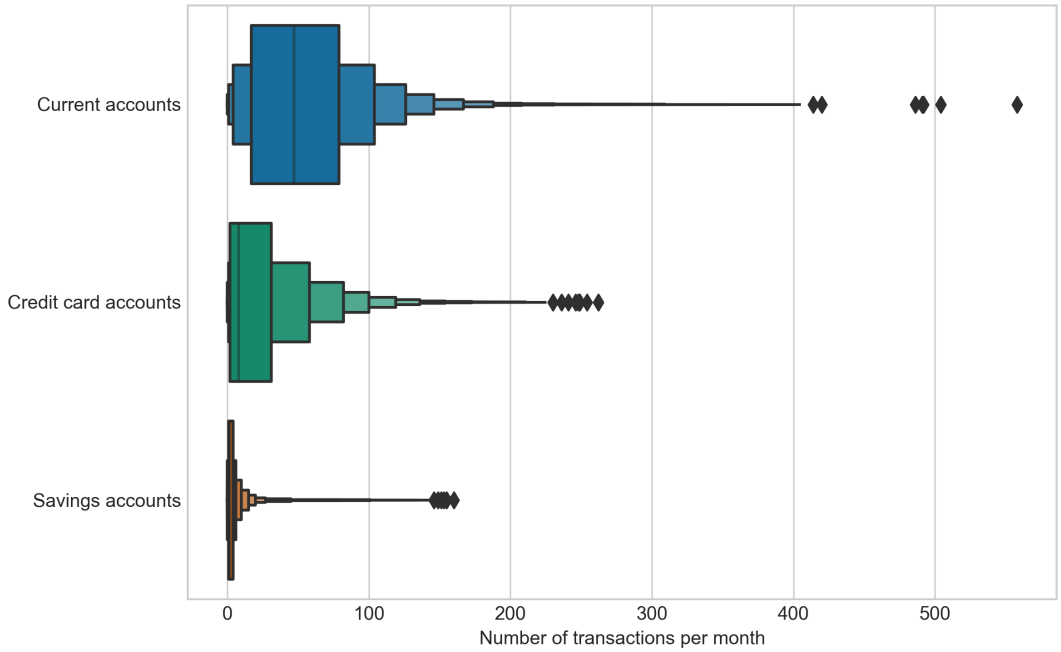


Figure 2: Monthly transactions by account type




Notes: The two innermost boxes in the letter-value plots are identical to those in a boxplot, with the center line corresponding to the median and the left and right edges to the first and third quartiles, respectively – or half of the remaining data on either side of the median. Additional boxes on either side extend that principle by corresponding to half of the remaining data on that side. For instance, the second box to the right of the median in the current accounts plot indicates that half of all account-month observations to the right of the third quartile have fewer than about 105 transactions. Boxes of the same height correspond to the same level, individually drawn observations are outliers.

Table 2: Summary statistics

| | count | mean | std | min | max | 25% | |
|---|---|---|---|---|---|---|---|
| obs | 163915 | 98.0689 | 51.2574 | 11 | 656 | 63 | |
| balance_ca | 159116 | 1130.2 | 4834.21 | -12257.1 | 34628.6 | -884.008 | 81 |
| balance_sa | 64935 | 2625.16 | 5496.73 | -1644.62 | 42168.6 | 2.21001 | |
| sa_inflows | 60583 | 780.844 | 1507.55 | 0 | 13800 | 60 | |
| sa_outflows | 60583 | 749.975 | 1452.1 | 0 | 12075.5 | 0 | |
| sa_net_inflows | 61195 | 75.7461 | 3330.15 | -69750 | 120000 | -180 | |
| sa_scaled_inflows | 59977 | 0.335841 | 0.548266 | 0 | 4.13782 | 0.0319006 | 0.1 |
| sa_scaled_outflows | 59977 | 0.332819 | 0.57624 | 0 | 4.03946 | 0 | 0.1 |
| sa_scaled_net_inflows | 59971 | 0.00713739 | 0.614697 | -4.03481 | 4.18434 | -0.0845304 | 0.008 |
| total_monthly_spend | 156510 | 7.28142 | 0.728324 | 4.95442 | 9.16108 | 6.81671 | 7. |
| tag_spend_household | 160635 | 0.349356 | 0.248708 | -0.840723 | 1.61585 | 0.174674 | 0. |
| tag_spend_hobbies | 160635 | 0.0116385 | 0.0231921 | -0.00630346 | 0.184913 | 0 | |
| tag_spend_retail | 160635 | 0.0598939 | 0.103136 | -0.620232 | 0.694001 | 0.00454646 | 0.03 |
| tag_spend_services | 160635 | 0.199177 | 0.174157 | -0.589876 | 1.08971 | 0.0882128 | 0. |
| tag_spend_other_spend | 160635 | 0.117678 | 0.196987 | -1.08001 | 1.50045 | 0.0189057 | 0.07 |
| tag_spend_finance | 160635 | 0.110878 | 0.155252 | -0.279174 | 0.871723 | 0.00624401 | 0.04 |
| tag_spend_travel | 160635 | 0.0552881 | 0.0956478 | -0.0688958 | 0.624166 | 0 | 0.01 |
| tag_spend_communication | 160635 | 0.0401485 | 0.0449402 | -0.0878466 | 0.320432 | 0.0115177 | 0.02 |
| tag_spend_motor | 160635 | 0.0388507 | 0.0528382 | -0.0443517 | 0.330336 | 0 | 0.01 |
| entropy_sptac | 160635 | 2.56947 | 0.215097 | 1.90212 | 2.99952 | 2.43239 | 2. |
| log_income | 163915 | 10.0934 | 0.580853 | 8.51758 | 12.1774 | 9.72488 | 1 |
| user_female | 154619 | 0.412259 | 0.492243 | 0 | 1 | 0 | |
| age | 149907 | 35.2528 | 10.9868 | 15 | 134 | 27 | |

### 2.4 Dependent variable

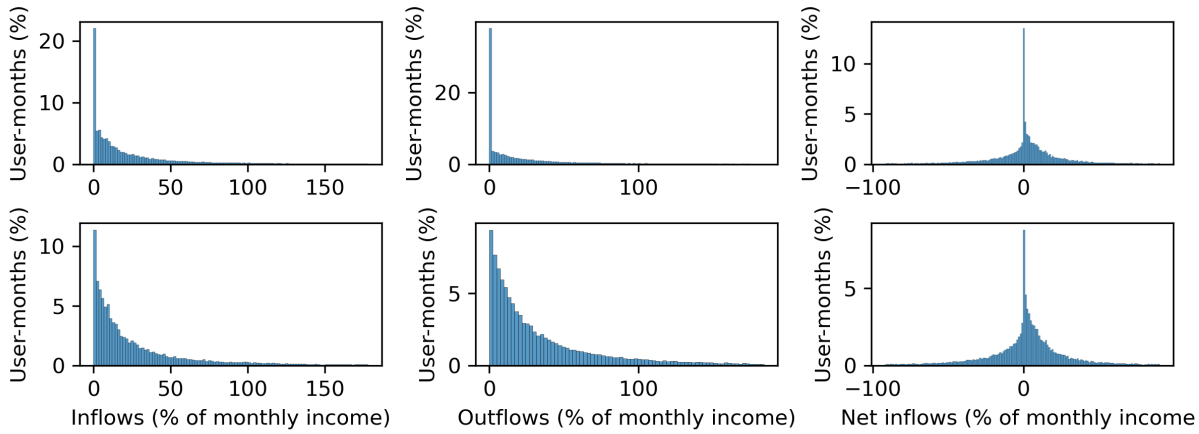
There is no single variable that captures an indiviual's monthly savings. Instead, we capture savings by looking at account balances and flows into savings accounts. Specifically, we focus on the following measures, each defined at the user-month level.

- Mean balance across all savings accounts
- Mean balance across all savings and current accounts
- Total inflows into savings accounts
- Net inflows (inflows minuts outflows) into savings accounts

todo: decide whether to scale inflows by monthly income

We calculate savings account inflows as the sum of all credits that are not identified as interest payments into a user's savings accounts. We would expect that it is particularly non-standing-order transactions into savings accounts that are related to entropy, and it might thus be reasonable to exclude standing orders. However, while we cannot perfectly identify standing orders, they seem to account only for a small proportion of all savings account transfers and are thus unlikely to affect our results. Because of that, we do not exclude them.

Figure 3: Monthly flows in and out of savings accounts




Notes: Flows are calculated for each user-month as the total inflows, outflows, and flows (calculated as inflows - outflows) into all of a users's savings accounts. Zero net flows represent months where inflows are either perfectly balanced by outflows or where there were no flows at all.

## 2.5 Independent variable

Spending entropy:

- We calculate spending entropy using the Shannon entropy $H$(Shannon 1948), defined as

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

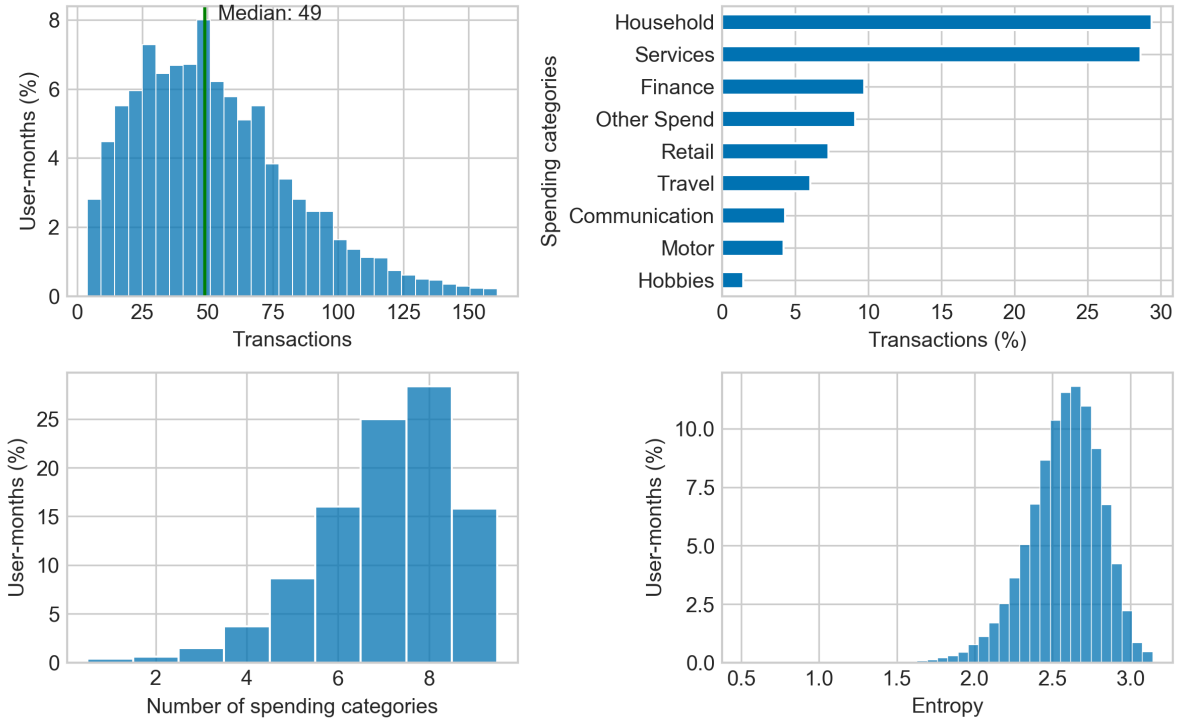
  where $p_i$ is the probability that an individual makes a purchase in spending category $i$, and $log$ is the base 2 logarithm. The measure can broadly be interpreted as the degree to which an individual's spending pattern is predictable, whith a higher score indicating less predictability.

- To calculate individual entropy scores, we group spending into 9 spending categories (SC), based on the classification used by Lloyds Banking Group as discussed in Muggleton et al. (2020).

- Also following that paper, when calculating $p_i$ we use additive smoothing and add one to the numerator and $N_{SC}$ to the denominator to avoid taking logs of zero counts in cases where an individual makes no purchases in a given spending category. $p_i$ is thus calculated as

$$p_i = \frac{\text{Count of purchases in } SC_i + 1}{\text{Count of all purchases} + 9} \tag{2}$$

Figure 4: Transactions distributions




Notes: From top-left to bottom-right: distribution of spending transactions per user-month, breakdown of spending transactions into spending categories; breakdown of number of spending categories spent on in user-month; distribution of user-month entropy scores.

### 2.6 Control variables

We calculate age as an individual's approximate age at the time of the transactions, by subtracting a user's year of birth from the year the transaction took place.

## 3 Methods

### 3.1 Model specification

$$s_{i,t} = \alpha_i + \lambda_t + \beta H_{i,t} + X'_{i,t}\delta + \epsilon_{i,t} \tag{3}$$

$s_{i,t}$ is individual $i$'s savings rate in month $t$, calculated as the total inflow of funds in month $t$ into all savings accounts held by $i$, divided by $i$'s estimated monthly income.

The vector of control variables, $X_{i,t}$, contains the monthly spend for each spending category, total monthly spend across all categories, and annual income.

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