**Evidence from mass-transactional data that chaotic spending behaviour
precedes consumer financial distress**

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Abstract

The prevalence of digital footprints can allow researchers to study the personalities of millions of individuals with improved ecological validity. We present spending entropy as a candidate personality trait derived as a feature of an objective big data source—mass-transactional data from millions of bank accounts. Entropy measures the unpredictability of spending and acts as a measure of the chaotic nature of a person’s life. Over and above how much money people spend, and what the money is spent on, spending entropy positively relates to future financial distress. High entropy leads to increased probability of missed payments across financial products. Entropy temporally relates to future distress three months ahead including more severe measures of distress. We replicate our findings in personal current account, loan, and mortgage holders in a second financial institution. Our findings suggest that high-dimensional data can be used to build psychological traits that predict outcomes in novel situations.

Significance Statement

Expanding on recent advances in detecting psychological traits from digital footprints, this paper explores whether mass-transactional data can be leveraged to infer individual differences. Using spending data from ~300,000 individuals in two separate financial institutions, we show that the chaotic nature of one’s daily spending (*behavioural entropy*) can improve judgements and predictions of novel, future events. Compared to self-report surveys, spending entropy has high ecological validity because digital footprints capture real-world behaviour, can be constructed for millions instead of hundreds or thousands of people, and provides a continuous measure over many years instead of a single snapshot.

Keywords: Behavioural entropy, personality traits, consumer psychology, financial decision-making, digital footprints

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Recently, the availability of high-dimensional data records has created new opportunities for researchers to study human behaviour in a natural, unobtrusive environment over extended periods of time. Traits have been inferred from social media activity (e.g., social networks: Bagrow, Liu, and Mitchell, 2019; Kosinski, Stillwell, and Graepel, 2013, text-based analysis: Bagrow et al., 2019; Park et al., 2015; or digital footprints: S. C. Matz, Kosinski, Nave, and Stillwell, 2017; Youyou, Kosinski, and Stillwell, 2015), mobile phone metadata (Ai, Liu, & Zhao, 2019; Blumenstock, Cadamuro, & On, 2015; Stachl et al., 2020), retail purchases (Guidotti, Coscia, Pedreschi, & Pennacchioli, 2015; Riefer, Prior, Blair, Pavey, & Love, 2017; Skatova, Stewart, Flavahan, & Goulding, 2020), and bank transactional data (Gladstone, Matz, & Lemaire, 2019; Landis & Gladstone, 2017; Sandra C. Matz, Gladstone, & Stillwell, 2016). These methods allow the researcher to study real-world decision-making in large samples, and can overcome potential experimenter and self-report biases (Park et al., 2015; Weston, Gladstone, Graham, Mroczek, & Condon, 2018; Youyou et al., 2015).

This literature suggests that digital records can be used to construct personality features that generalise across domains, creating features that predict real-world outcomes. We extend this research by developing a new feature of individual behaviour: the *unpredictability* of spending behaviour. In the present report, we examine the relationship between traits of chaotic behaviour and real-world outcomes.

In many situations, human behaviour is ordered. Individuals have a preference for stable patterns of behaviour when planning their daily coordination tasks (Kelley, Shillingsburg, & Bowen, 2016), grocery shopping (Riefer et al., 2017), and commuting (Lattarulo, Masucci, & Pazienza, 2019). Disordered behaviour is considered maladaptive: chaotic environments are associated with worse executive function (e.g., working memory, attention skills, mental flexibility; Vernon-Feagans, Willoughby, and Garrett-Peters, 2016),

impaired cognitive inhibition (Mittal, Griskevicius, Simpson, Sung, & Young, 2015), and activation of anxiety-related neural circuits (Hirsh, Mar, & Peterson, 2012). The pathway from unpredictable lifestyles to negative outcomes has been variously attributed to individuals blocking out and withdrawing from chaotic environments (Wachs & Evans, 2010), activating neurophysiological markers of anxiety (Hirsh et al., 2012), and promoting impulsive behaviour (Frankenhuis, Panchanathan, & Nettle, 2016).

The extent to which behaviour is ordered and predictable can be captured using the information theoretic concept of entropy. Entropy is a familiar concept to physical scientists and mathematicians, and there is a broad multiple-domain literature on entropy (Crupi, Nelson, Meder, Cevolani, & Tentori, 2018). Statistical entropy has been used to shed light on the dynamics of email communication (Eckmann, Moses, & Sergi, 2004) and has previously been hypothesised to be a feature of economic systems more generally (Kümmel, 2011). At the level of the individual, spending entropy predicts high spend in, and more frequent visits to, the supermarket (Guidotti et al., 2015), as well as higher caloric intake (Skatova et al., 2020).

We predicted that high spending entropy would be associated with an increased risk of subsequent financial distress, as suggested by the relationship between chaotic lifestyles and impaired cognitive functioning (Frankenhuis et al., 2016; Mittal et al., 2015; Vernon-Feagans et al., 2016). We explore this by measuring spending entropy and subsequent credit card delinquency in a sample of 190,429 credit card holders in the Argus Credit Card Payments Study. We then replicate and extend our analysis to personal current account (PCA), loan, and mortgage delinquency in a sample of 100,659 customers at Lloyds Banking Group (LBG), which is the UK's largest retail bank. In both analyses financial distress is measured at two levels: less severe financial distress where an individual who has otherwise kept up with his or her monthly payments misses one payment due on the product, and more severe financial distress where the individual misses two or more payments due on the product.

Specifically, we examine the relationship between entropy in individual spending patterns across types of spending and future financial distress. Entropy is, for a distribution over categories, the analogue of the variance of the distribution of a continuous number. We measure the Shannon entropy (Shannon, 1948) of spending over product and service categories (e.g., retail spending, household bills, hobbies and interests, travel). We show that there is wide variation in the degree of randomness in individual spending. Whereas some individuals exhibit low entropy, with their transactions concentrated in a few predictable categories, others exhibit high entropy with transactions spread over multiple categories in the data in difficult-to-predict patterns. These differences reflect differing degrees of complexity in individuals' financial lives. Changes in entropy reflect experiences that alter the shape of the individuals' spending probability distributions and could precede future events of financial distress.

Method

Sample

Data Sources

Data are drawn from two sources. First, we draw a random sample of credit card holders from the Argus Credit Card Payments Study ("Argus"). The Credit Card Payments Study dataset collates statement data from all credit card providers in the United Kingdom. The sample we use has detailed information on contract terms and billing records from five major credit card issuers. These issuers have a combined market share of over 40% and represent a broad range of credit card products and market segments. We have obtained monthly data covering January 2013 to December 2014 for a 10% representative sample of individuals in the Argus dataset who held a credit card with at least one of the five issuers. The data sample comprises 1.4 million individuals and 1.8 million individual credit cards. In addition, Argus provided geocodes in the form of 4-digit UK postcodes, which allows us to match geographically-granular census micro-data to our

credit card panel and identify the socio-economic characteristics of the credit card holders—median house prices, weekly income, and the proportion of children in the locality entitled to free school meals.

Second, we draw a random sample of retail customers of Lloyds Banking Group (LBG). LBG is the United Kingdom’s largest retail bank, offering a broad range of financial services including PCAs, mortgages, credit cards, and savings products. LBG has over 31 million UK customers across its three main brands (Lloyds Bank, Halifax, and Bank of Scotland). The data cover the 2018 calendar year.

Sample Restrictions

In both samples, we restrict our analysis to accounts with non-zero transaction volumes, excluding dormant or rarely used accounts in which we see few or no transactions. The steps in sample construction and data cleaning for both datasets are described in Table S1 and summarised briefly below.

Argus. As part of the sample restrictions and data cleaning, we exclude corrupted accounts, defined as accounts with multiple open dates, accounts with multiple (different) monthly end dates, accounts with unknown minimum payments, accounts with negative balance, and accounts with truncated transaction data. We also excluded accounts with balance transfers.

Because our measure of entropy in the Argus sample uses patterns of consumption for an interval of six months, we included only accounts registering at least one transaction in each of these months. We excluded accounts that recorded transactions in only one merchant category (MC) during this period, which suggests that the cardholder has other alternative means to pay for their consumption. Our final sample included 190,429 individuals and 197,179 credit cards with a median value of the transactions per month of £500.

LBG. We first identified all unique individuals who banked with Lloyds Bank, Halifax, and / or Bank of Scotland, and who were identified by LBG as active during 2018,

resulting in a sample of over 24 million distinct individuals. Next we excluded individuals whose product portfolio consisted only of non-transactional accounts. For example, if a customer had a loan or mortgage with LBG, but neither a PCA nor credit card, the individual was excluded ($N_{\text{customers}} = 21$ million). To gain a holistic view of individuals' transactional history, we joined each individual's PCA(s) and credit card account(s). A *personal current account (PCA)* is the UK equivalent of a checking account in the US and elsewhere. For each credit card, the median number of transactions was 51 (mean = 103.1) per month. For each debit card, the median was 248 (mean = 330.78) per month. We used LBG's definition of an active customer as an individual whose accounts process at least twelve transactions per month. This definition was constructed independently of the authors and prior to the analysis commencing. It avoids including cases where individuals hold dormant bank accounts. This resulted in a sample of 9.1 million individuals. We randomly selected 1 in 90 individuals and matched in financial distress data, resulting in a final sample of 100,963 individuals.

Design

Dependent Variables

We constructed two sets of outcome variables highlighting different degrees of financial distress. The first set of outcome variables identify when the individual missed a payment due by a specified date (e.g., a credit card bill due date) or exceeded a credit limit once within the month. We denote these events as *missed one payment* and they represent less severe financial distress. The second set of outcome variables identify when the individual misses two payments in succession (e.g., also misses their credit card payment by the next due date after the first missed payment) or exceeded a credit limit two months in a row. We denote these events as *missed multiple payments* and they represent more severe financial distress as the individual falls further behind with payments, thereby accruing additional penalty charges and negative credit file flags. As such, all multiple missed

payments begin with one missed payment. These two sets of outcomes are measured for credit cards, PCAs, personal loans, and mortgages.

Specifically, outcomes are measured for each product as follows. *Credit Card*: a missed payment denotes the individual failing to pay at least the minimum payment due on the account. *PCA*: exceeding the overdraft limit. *Personal Loan*: a missed payment denotes the individual failing to pay the instalment payment due on the account. *Mortgage*: a missed payment denotes the individual failing to pay the payment due (either for capital repayment or interest) on the account.

We further separate the credit card data into two groups by whether the card was paid by direct debit or paid manually. Individuals adopting an autopay setting are insuring themselves against future forgetting payments. Hence, missing payments in this sample reflect higher degrees of financial constraints. Table 1 provides summary statistics for our outcome variables. The most common form of financial distress is missing a manual (non-Direct Debit) credit card payment. We also observe that some forms of financial distress are very rare, such as missing two consecutive automatic (Direct Debit) credit card payments.

Independent variable

Our independent variable of interest is the entropy score over the spending across a number MCs. Entropy captures the predictability of outcomes drawn from distributions over categories like those observed in Figure 1. We calculate Entropy using the Shannon entropy H , defined as:

$$H = -\sum p_i \log_2(p_i), \quad (1)$$

where p_i is the probability that an individual carries out a transaction with MC i . A larger H represents less predictable spending across merchant categories.

Figure 1 illustrates how entropy scores are calculated at a monthly level,

Table 1

Summary statistics for financial distress, as a function of dataset, product, and outcome severity.

Dataset	Product	N_{missed}^*	$N_{\text{customers}}$	N_{obs}	Total missed	M	SD
Argus	CC (no DD)	1	122,746	1,388,002	17,389	.013	.11
		2+	120,906	1,307,362	1,655	.0013	.036
	CC (DD)	1	68,448	782,718	2,396	.0031	.055
		2+	67,122	735,764	383	.00052	.023
	CC (no DD)	1	16,292	164,891	1,539	.0093	.096
		2+	15,988	149,245	240	.0016	.040
	CC (DD)	1	10,850	100,630	632	.0063	.079
		2+	10,650	91,478	47	.00051	.023
	PCA	1	94,175	667,857	2,011	.0030	.055
		2+	93,747	596,778	879	.0015	.038
	Loan	1	5,226	37,577	182	.0048	.069
		2+	5,212	33,592	105	.0031	.056
	Mortgage	1	6,145	43,314	251	.0058	.076
		2+	6,140	38,987	158	.0041	.064

*Number of missed payments at $t = 1$

represented by three example customer months at the 25th, 50th, and 75th percentiles of the entropy distribution. Each individual has 47 transactions but differs in the distribution of transactions across spending categories, with the coloured circles denoting the number of transactions in each category. Whereas the low-entropy individual has almost all transactions in one category (retail), the high-entropy individual has a distribution that is more spread across transaction categories.

p_i is the probability that an individual carries out a transaction within MC i . The MC codes used in our analysis are defined by the financial product providers. The Argus dataset contains 27 MCs and the LBG dataset contains nine MCs. To avoid taking logs of 0 counts (i.e., no purchases within a given MC), we used Laplace smoothing and added one to the numerator and $1 \times N_{\text{MC}}$ to the denominator. For example, when there are 27 MC available then the probability p_i is:

$$p_i = (\text{Count of purchases in MC}_i + 1) / (\text{Count of all purchases} + 27). \quad (2)$$

Figure 1

Computation of Entropy. The top histogram illustrates the distribution of entropy scores in the LBG sample. The positions of three example individual months are highlighted at the 25th (low), 50th (medium), and 75th (high) percentiles of the entropy distribution. We selected individual months with exactly 47 transactions, the mean number of monthly transactions. The individual months differed in the distribution of transactions across spending categories, as the plots below of the three example individual months show. Each row represents a separate transaction category, with the coloured circles denoting the number of transactions in that category. The low-entropy individual month (blue) has almost all transactions in one single category, but the high-entropy individual month (tan) has a distribution that is more spread across transaction categories. The medium-entropy individual month (green) represents the mean level of entropy in the sample.

In the Argus dataset, where we calculate entropy scores across spend in only credit card accounts, monthly spend is comparatively sparse. To include a sufficient number of MCs per individual and be able to distinguish spending patterns, we computed a six-month entropy measure—entropy is computed for every month but represents chaotic spending across the past six months of transactions. Our results, nevertheless, are not sensitive to reasonable departures from this specific interval of months. As such, the data contain one entropy score per account, per month, in the Argus dataset. In the LBG dataset, however,

we aggregate spend across both PCA and credit card accounts to give a more comprehensive view of monthly spend. As such, entropy scores in the LBG dataset are calculated per customer, per month.

Model specifications

The outcome variables in our analysis are the measures of financial distress, defined over four product types. We estimate models taking two forms.

Model 1: Missed one payment.

$$\text{one missed}_{i,t=1} = \beta_0 + \beta_1 H_{i,t=0} + \omega X_{i,t=0} + \epsilon_{i,t=1} \quad (3)$$

$$\text{one missed}_{i,t=1} = \beta_0 + \beta_1 H_{i,t=-2} + \omega X_{i,t=-2} + \epsilon_{i,t=1} \quad (4)$$

where $\text{missed}_{i,t=1}$ is a dummy variable indicating one missed payment for a specific financial product (credit card, PCA, personal loan, or mortgage), by individual i in month $t = 1$, $\text{entropy}_{t=0,i}$ is the standardised entropy score for the individual's transactions in the preceding month, $X_{i,t=0}$ is a set of covariates in the preceding month and $\epsilon_{i,t=1}$ is the error term. The first equation measures entropy at $t = 0$ whereas the second equation measures entropy at $t = -2$ in order to test whether entropy predicts future missed payments over a longer time horizon.

Model 2: Missed two payments.

$$\text{two missed}_{i,t=1} = \beta_0 + \beta_1 H_{i,t=0} + \omega X_{i,t=0} + \epsilon_{i,t=1} \quad (5)$$

$$\text{two missed}_{i,t=1} = \beta_0 + \beta_1 H_{i,t=-2} + \omega X_{i,t=-2} + \epsilon_{i,t=1} \quad (6)$$

where the only variation from Model 1 is that the independent variable now indicates two

missed payments. In addition, we also estimate models that include an individual-specific fixed effect. These models are estimated on the LBG data only, because the lower-frequency six-monthly measure of entropy does not have sufficient within-individual variation.

The vector of control variables X_i includes total monthly spending in each MC plus, i) in the Argus data, controls for total monthly spending in each MC plus account tenure, credit card Annualised Percentage Rate (APR), credit limit, utilisation, local house prices, incomes, and the proportion of households in the locality receiving free school meals, and ii) in the LBG data, controls for spending by channels (cash, direct debit, debit card), gender, age, and annual income. In all models, we take into account the clustered nature of the sample. Standard errors are clustered by account in the Argus dataset—to exploit the fact that control variables are at account level—and by individual in the LBG dataset. All models control for seasonal patterns of spending/repayment behaviour by including month fixed effects. We also estimate models that include an individual-specific fixed effect. In the Argus data set, to control for total monthly spending on each MC, we computed Principal Component Analysis with orthogonal varimax rotation over the proportions spent on each of the 27 MCs present in the data. Our regressions incorporate these principal components on MC expenditure, while controlling also for the total monthly expenditure. Because the LBG data contained fewer categorisations, clustering was not used and the proportion spent on each of the nine categories was inputted as a control variable.

In both models, we restrict the sample to observations for which there is no missed payment in month $t = 0$. This additional restriction is applied to avoid a potential problem of reverse causation if missed payments caused individuals to change their spending patterns.

We estimate models for seven product types (Argus manual payment credit card, Argus automatic payment credit card, LBG manual payment credit card, LBG automatic payment credit card, LBG PCA, LBG personal loan, and LBG mortgage), with two outcomes per product (missed once and missed twice), entropy measured at two points in

time ($t = 0$ and $t = -2$), and specifications with and without individual fixed effects. Estimates are displayed across Table S11–Table S51. To ease their interpretation, the tables describe the effects of changes in entropy occurring at $t = 0$ in financial distress outcomes occurring in the subsequent months.

Results

In Figure 2, we observe the distributional plots of the number of transactions, number of MCs, and entropy scores for the sample of Individual $\times$ Months used in the analysis. Although the absolute entropy scores are not directly comparable across the two samples (see Methods section for an outline of structural differences between datasets), the entropy score distributions are similar in both datasets.

Figure 3 is ordered left-to-right in the order that the analyses were conducted. The Argus credit card samples are shown in blue, with the LBG samples shown in green. We standardise entropy to ease the interpretation of the coefficients.

Because defaulting payments constitute very infrequent events (but with potentially serious consequences), to evaluate the actual importance of entropy changes in determining future financial distress, we calculated effect sizes relative to the average probability of missing one (or more) payments in each of our regression samples. Figure 3 summarises the results obtained by OLS estimators.

The effect sizes shown in Figure 3 represent changes in the probability of default with respect to the probability observed for an average individual in the sample (i.e., when all covariates are at their sample mean). To illustrate the degree of variation in entropy that is attached to these effect sizes, an increase in one standard deviation in the entropy score is approximately equivalent to the change in the expenditure patterns from the distribution displayed in the left blue panel of Figure 1 to the distribution displayed in the middle green panel (or from the distribution in the middle green panel to the distribution in the right tan panel).

Figure 2

Transaction Distributions. Figure illustrates distributions of number of transactions per month (left-panel), transactions by MC (middle-panel), and entropy score (right-panel). Unit of observation is an Individual $\times$ Month. LBG transaction plot excludes transactions $> 99\%$ percentile ($N = 136$). Note. Entropy scores in the Argus and LBG datasets are not comparable because (i) Argus (LBG) dataset contained 27 (9) possible MCs, (ii) entropy was calculated across six months' (one months') worth of transactions in the Argus (LBG) dataset, and (iii) entropy was calculated using only credit card (credit card and PCA) transaction data in Argus (LBG).

In Figure 3, the effect sizes of entropy are positive and precisely defined in most of the models. Entropy is a predictor of short term (missing the next payment) financial distress for credit cards with autopay in both Argus and LBG datasets. But changes in entropy appear to precede short term financial distress and also more severe financial distress (missing two consecutive payments) for PCA, loans, and mortgages, where one

Figure 3

Effect Sizes. The estimated effect of one standard deviation increase in entropy as a percentage change in probability of missing one payment (top row) and, separately, missing two consecutive payments (bottom row) for seven financial products. All estimates are reported after controlling for spending behaviour and the demographic variables outlined in Table S11–Table S51. Entropy is standardised, such that $M = 0$ and $SD = 1$. For each model, the standardised entropy coefficient is divided by the baseline probability to estimate the effect of increasing entropy by one standard deviation. For example, this means that a one standard deviation increase in standardised entropy at $t = 0$ (i.e., moving from a standardised entropy value of 0 to 1) increases the likelihood of missing a loan repayment at $t = 1$ from 0.48% to 0.62%, an increase of 28.07% (top row, Loan column, black point). Blue panels show estimates from Argus dataset, green panels show estimates from LBG dataset. Within each panel, the black coloured dots indicate estimates from models in which entropy is computed at $t = 0$ (predicting missing a payment one month ahead) and, in the tan coloured, estimates in which entropy enters at $t = -2$ (predicting missing a payment three months ahead).

standard deviation increase in entropy raises the probability of missing future payments by more than 10%. For these financial products, changes in entropy predict severe financial distress one month ahead and even three months ahead. These empirical regularities

suggest that fluctuations in entropy are generally associated with an increased likelihood of future financial distress and are not specific to a few financial products.

Parameter estimates used in the computation of the effect sizes in Figure 3 are shown in Table 2. These estimates correspond to the models that include the full set of control variables described earlier (Tables S4 to S51, last column) and represent the absolute percentage point change in the probability of default associated with a one standard deviation increase in entropy. Table 2 also presents fixed effects estimators. The OLS estimates reported above made use of the variation in spending patterns over time and across account holders to measure the effect of entropy in future financial distress. Although we observe a positive and consistent association, it is possible that this association reflects, to a larger extent, differences across account holders. In fact, as both panel datasets used in this study are relatively short, differences across individuals, rather than changes within an individual over time, have more influence on our financial distress outcomes. Including individual fixed effects causes the coefficient estimates to attenuate and lose precision.

The finding that fixed effects estimators show much smaller and imprecise entropy coefficients is consistent with the concept of entropy as a trait-like characteristic, rather than a temporary state of chaotic spending behaviour, that is associated with a higher risk of future financial distress. Our data, however, do not allow us to test these two alternative views given the absence of a longer time horizon that permits a more comprehensive analysis of the stability of entropy scores within individuals.

Figure 3 shows much larger immediate effects of entropy changes on missing payments for loans and mortgages than for exceeding overdraft limits. However, effects on payments attached to credit cards are of small magnitude and non-consistent across both datasets (effects appear only apparent for payments linked to direct debit credit cards). Loan and mortgage payments are usually much larger than those associated with credit cards and borrowers have usually much stronger incentives to make regular payments given

Table 2

Summary of regression coefficients and p-values, as a function of dataset, product, outcome severity, and entropy lag.

Dataset	Product	N_{missed}	t_{obs}	Coef. * 100	95% CIs	p-value
Argus	CC (no DD)	1	0	.074	(.051, .097)	<.001
			-2	.097	(.073, .121)	<.001
		2+	0	-.00049	(-.0068, .0058)	.880
			-2	.0010	(-.0060, .0080)	.782
	CC (DD)	1	0	.022	(.0080, .036)	.003
			-2	.028	(.013, .044)	<.001
		2+	0	.0012	(-.0043, .0067)	.679
			-2	.0030	(-.0032, .0092)	.347
LBG	CC (no DD)	1	0	-.032	(-.082, .018)	.206
			-2	-.030	(-.099, .040)	.400
		2+	0	-.010	(-.034, .013)	.394
			-2	-.030	(-.054, -.006)	.014
	CC (DD)	1	0	.146	(.093, .199)	<.001
			-2	.163	(.090, .236)	<.001
		2+	0	.019	(.0029, .036)	.021
			-2	.049	(.027, .071)	<.001
	PCA	1	0	.036	(.022, .049)	<.001
			-2	.046	(.029, .062)	<.001
		2+	0	.047	(.034, .059)	<.001
			-2	.031	(.019, .043)	<.001
	Loan	1	0	.136	(.060, .212)	<.001
			-2	.188	(.085, .292)	<.001
		2+	0	.128	(.060, .196)	<.001
			-2	.093	(.025, .162)	.007
	Mortgage	1	0	.104	(.030, .179)	<.001
			-2	.135	(.043, .228)	.006
		2+	0	.157	(.083, .232)	.004
			-2	.103	(.029, .178)	.007

the potential adverse consequences—not meeting credit card payments will not put individuals' homes at risk. The finding that default rates on loans and mortgages are particularly sensitive to entropy changes suggest that entropy might help to identify those individuals who are at greater risk of experiencing severe financial distress.

The variation of the effect sizes shown in Figure 3 also suggests that there might be substantial heterogeneity among individuals acquiring each of these financial products. But it is also consistent with the view that different financial products target different segments

of the market.

The effect of control variables are reported in Tables S4 to S11. They show that the risk of missing an incoming payment decreases with the account age but is not affected by either market interest rates or credit limit changes. In fact, past spending patterns (captured here by entropy scores) appear to play a much larger role in determining defaults than both interest rates or credit limits. Demographic variables across Tables S12 to S51 reveal that only the individuals' age has a negative correlation with missing future payments, whereas neither gender nor income are statistically significant or show consistent signs across the different sets of regressions.

We have reported above all of the analyses carried out and in order the analysis was conducted. Although the analyses conducted in the two datasets are not directly comparable, results from both datasets demonstrate that unpredictability of spending precedes events of short-term and even longer-term financial distress. To illustrate the importance of the effect of changes in entropy in spending, a one standard deviation increase in entropy raises the probability of default in direct debit credit cards by 0.02 percentage points. This difference is not trivial in economic terms. For example, the estimated reduction in monthly expenditure (probably signalling liquidity constraints) that would be necessary to achieve the same change in the probability of missing an incoming credit card payment as would a change in an individual's entropy is £200. Or even more sharply, the estimated reduction in monthly expenditure that would equate the effect of entropy on the probability of missing a loan payment is of about £3,300. (We make this correlational comparison based on the estimated coefficients in Table S8, column 4, and Table S24, column 2.)

Discussion

Here we have used detailed data on individual transactions drawn from bank accounts and credit card records to examine the relationship between entropy in spending

behaviour and future financial distress. Statistical entropy as a data feature is well-known within the field of applied statistics. Here we show that it also captures a feature of individual spending behaviour associated with future financial distress. Importantly, this effect is positive and precisely defined in models that condition upon the level of spending and associated covariates. The two datasets used in the analysis allow us to control for a range of confounds. The Argus data include additional information on the product-specific APR, demographic controls, and detailed product category data. The LBG data provide additional information on spending channels.

We suggest that the relationship between entropy and future financial distress may reflect a role for more complex spending behaviour in raising the likelihood of distress. Higher entropy in spending categories may reflect a more complex, chaotic lifestyle on the part of the account holder. This might explain why, even when low- and high-entropy account holders exhibit the same level of expenditure, a high-entropy account holder is more likely to miss a repayment. Entropy as a feature of spending data may prove useful to financial product providers, or regulators, who seek to understand the drivers of financial distress.

This paper has some limitations that could be addressed with further study. Because the observation window is relatively short, we cannot, for example, test whether entropy is a stable trait, or whether within-person changes in entropy precede financial distress. Second, although our baseline sample restrictions attempt to capture individuals for whom we have a comprehensive view of financial behaviour (Supplementary Table S1), we cannot rule out the possibility that individuals use other financial products that are unseen by Argus and LBG. Third, the present report tests the association between behavioural entropy and future financial distress among individuals with no recent history of poor financial health. As such, the results may not generalise to the probability of individuals who are in financial distress are more likely to ‘self-cure’ or enter an increasing cycle of debt. Finally, for some products we see higher effects of entropy, which could be the result

of particular products attracting different segments of the market, via self-selection biases.

The approach adopted in this paper of exploring a statistical construct (here, entropy) differs from approaches that seek to automatically create features from high-dimensional data sets, such as deep learning (LeCun, Bengio, & Hinton, 2015). An interesting question for future research is the relationship between features learned by machine-learning algorithms and features derived from statistical constructs, in particular whether and how machine-learning algorithms effectively discover such constructs.

Transparency

Author Contributions

Authors 2 and 5 proposed the initial concept. All authors contributed to the design of the analysis and the interpretation of the results. Authors 1 and 2 constructed variables and prepared all figures and tables. Author 3 wrote the initial draft, Author 1 conducted a review of the existing literature, and Author 2 wrote up the results. All authors contributed to the revision. Author 4 established collaboration with LBG. Authors 3, 4, and 5 secured funding for the research.

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Open Practices

Argus and LBG data cannot be available in an openly accessible data repository. For peer review purposes, we can provide access to the data for the purpose of running the code in order to replicate our results. This can be achieved via virtual private network access to the local server on which the data are stored (and on which the analysis is run) under supervision of one or more of the authors of the paper. We may also be able to

provide local access to an independent researcher on site at the University of Warwick or University of Oxford. Data were extracted from LBG databases using Teradata SQL Assistant (Version 15.10.1.9). Data analysis was conducted using R (Version 3.4.4). The R code used to construct the analysis conducted in the Argus dataset can be available under request. The R and SQL code that supports the analysis in the Lloyds dataset are available from LBG but restrictions apply to the availability of this code, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of LBG and Argus. The design and analysis plans for this study were not preregistered.

Supplemental Material

Additional supporting information are available for this paper.

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Supplemental Online Material

Supplementary Table S1*Baseline sample restrictions.*

Step	Description	$N_{\text{customers}}$	N_{accounts}	$N_{\text{transactions}}$	Value (£'000 000s)	% transactions
<i>Panel A: Lloyds Banking Group</i>						
.	Initial sample	35 140 086	55 626 331	...	...	...
1.	Account status = Open	31 826 995	46 696 843	20 388 631 386	1 598 852.78	100.00
2.	Account = PCA or credit card	22 696 677	25 334 095	19 092 022 058	1 493 189.02	93.64
3.	Customer-generated transactions	20 521 092	18 987 100	9 801 121 397	896 892.02	48.07
4.	Primary customers	16 329 592	18 987 100	8 028 187 321	694 426.10	39.38
5.	12+ monthly transactions	12 270 705	12 618 352	7 656 316 426	596 989.72	37.55
6.	Random subset	100 659	104 511	45 004 133	4942.37	0.22
<i>Panel B: Argus</i>						
<i>DD Accounts</i>						
.	Initial sample	180 210	191 349	38 398 378	1959.13	100
1.	$N_{\text{transactions}} > 0$ and $N_{\text{merchant categories}} > 1$ in the preceding 6 months	117 902	121 903	27 815 474	1353	72.44
2.	Exclude missing due minimum payment in following month	116 583	120 481	26 031 899	1270.89	67.79
3.	Remove observations with missing entropy value	115 078	118 815	25 950 665	1267.96	67.58
4.	Exclude outliers in monthly expenditure (1%, 99%)	109 760	113 166	23 095 118	1078.46	60.15
5.	Demographic controls missing	68 448	70 769	13 219 582	638.53	34.43
<i>No DD Accounts</i>						
.	Initial sample	319 388	336 598	57 043 342	2980.17	100
1.	$N_{\text{transactions}} > 0$ and $N_{\text{MCs}} > 1$ in the preceding 6 months	205 450	211 473	41 191 821	2032.18	72.21
2.	Exclude missing due minimum payment in following month	203 102	208 974	38 501 057	1907.83	67.49
3.	Remove observations with missing entropy value	201 400	207 099	38 381 200	1902.44	67.28
4.	Exclude outliers in monthly expenditure (1%, 99%)	195 232	200 561	35 305 106	1673.02	61.89
5.	Demographic controls missing	122 746	126 410	19 993 420	972.38	35.05
<i>All Accounts</i>						
	Final sample	190 429	197 179	33 213 002	1610.91	34.8

Supplementary Table S2*Summary statistics for the LBG dataset.*

Variable	<i>M</i>	<i>SD</i>	<i>p</i> 50	Min	Max
Independent variable					
Entropy (past month)	1.93	0.39	1.93	0.14	3.11
<i>What individuals spend (£'000s)</i>					
Month spend	2.12	2.84	1.50	.02	556.54
Communication	.08	.08	.06	0	22.46
Financial services	.52	2.12	.16	0	552.83
Hobbies & interests	.09	.85	.01	0	347.00
Household bills	.13	.20	.06	0	37.43
Miscellaneous	.04	.49	.00	0	360.04
Motor	.13	.61	.04	0	60.08
Retail	.68	.67	.45	0	94.50
Services	.07	.37	.00	0	46.50
Travel	.10	.39	.00	0	73.81
Other	.27	.39	.16	0	19.82
<i>How individuals spend (£'000s)</i>					
ATM	.27	.38	.15	0	14.10
Credit card	.12	.48	.00	0	100.12
Direct debit	.57	1.28	.32	0	459.56
Debit card	1.17	2.29	.70	0	551.27
<i>Demographics</i>					
Age	44.45	17.04	43.00	18	104
Annual income (£'000s)	38.46	85.76	25.84	−.23	15473.31

Supplementary Table S3*Summary statistics for Argus dataset*

Variable	<i>M</i>	<i>SD</i>	<i>p</i> 50	Min	Max
Independent variable					
Entropy (past 6 months)	3.79	0.47	3.85	0.44	4.68
<i>Account Characteristics</i>					
Account Tenure (years)	11.16	9.55	8.10	0.35	42.45
Month Spend (£'000s)	0.74	0.76	0.50	0.01	5.15
Merchant APR (%)	17.34	4.59	17.95	0.00	34.90
Credit limit (£'000s)	6.72	4.02	5.90	0.00	80.00
Utilisation (ending balance/ credit limit) (%)	20.85	24.06	11.82	−467.25	1335.00
<i>What individuals spend (£'00s)</i>					
Airlines	0.16	1.28	0.00	0.00	49.07
Auto rental	0.04	0.41	0.00	0.00	47.49
Hotel/motel	0.34	1.51	0.00	0.00	47.66
Restaurants/bars	0.43	1.09	0.00	0.00	50.00
Travel agencies	0.23	1.72	0.00	0.00	50.19
Other transportation	0.19	0.96	0.00	0.00	50.22
Department stores	0.19	0.85	0.00	0.00	49.10
Discount stores	0.05	0.30	0.00	0.00	38.04
Clothing stores	0.38	1.04	0.00	0.00	46.07
Hardware stores	0.30	1.35	0.00	0.00	50.09
Drug stores	0.06	0.22	0.00	0.00	34.52
Gas stations	0.65	1.02	0.17	0.00	48.54
Mail orders	0.25	0.87	0.00	0.00	47.08
Food stores	1.39	2.04	0.47	0.00	44.22
Vehicles	0.32	1.51	0.00	0.00	50.66
Interior furnishing stores	0.26	1.50	0.00	0.00	50.00
Electric appliance stores	0.21	1.16	0.00	0.00	48.91
Sporting goods/toy stores	0.12	0.65	0.00	0.00	45.59
Other retail	0.56	1.44	0.10	0.00	50.37
Health care	0.16	0.98	0.00	0.00	50.73
Recreation	0.21	0.94	0.00	0.00	47.29
Education	0.04	0.58	0.00	0.00	48.85
Utilities	0.07	0.45	0.00	0.00	38.77
Professional services	0.33	1.34	0.00	0.00	50.00
Repair shops	0.01	0.17	0.00	0.00	49.99
Other services	0.43	1.52	0.00	0.00	51.26
Quasi cash	0.03	0.50	0.00	0.00	50.00
<i>Demographics</i>					
Median house price (£'000,000s)	0.23	0.12	0.20	0.05	2.75
Weekly income (£'000)	0.79	0.16	0.76	0.37	1.42
Proportion of free school meals (%)	11.11	6.48	9.65	0.00	48.13

Supplementary Table S4

Predicting whether an individual in the Argus dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.002 (0.001, 0.002) $p < .001$	0.001 (0.001, 0.001) $p < .001$	0.001 (0.0004, 0.001) $p < .001$	0.001 (0.001, 0.001) $p < .001$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.0002 (-0.0002, -0.0002) $p < .001$	-0.0002 (-0.0002, -0.0002) $p < .001$	-0.0002 (-0.0002, -0.0002) $p < .001$
Month Spend (£'000s)		-0.005 (-0.005, -0.004) $p < .001$	-0.007 (-0.008, -0.006) $p < .001$	-0.007 (-0.008, -0.006) $p < .001$
Merchant APR (%)		0.0002 (0.0002, 0.0003) $p < .001$	0.0002 (0.0002, 0.0003) $p < .001$	0.0002 (0.0001, 0.0003) $p < .001$
Credit limit (£'000s)		0.0003 (0.0002, 0.0004) $p < .001$	0.0003 (0.0002, 0.0004) $p < .001$	0.0003 (0.0002, 0.0003) $p < .001$
Utilisation (ending balance/ credit limit) (%)		0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$
<i>How individuals spend</i>				
PC1: Food Stores / Gas Stations			-0.0004 (-0.001, 0.00002) $p = .064$	-0.0003 (-0.001, 0.0001) $p = .096$
PC2: Department Stores / Clothing Stores			0.001 (0.0002, 0.001) $p = .001$	0.0004 (0.00004, 0.001) $p = .027$
PC3: Hotel/ Restaurants/ Other Transportation			0.001 (0.001, 0.002) $p < .001$	0.001 (0.001, 0.001) $p < .001$
PC4: Professional Services / Other Services			0.001 (0.001, 0.002) $p < .001$	0.001 (0.001, 0.001) $p < .001$
PC5: Interior Furnishing Stores			0.001 (0.0003, 0.001) $p < .001$	0.001 (0.0004, 0.001) $p < .001$
PC6: Sporting Goods/ Recreation			0.001 (0.0003, 0.001) $p < .001$	0.001 (0.0003, 0.001) $p < .001$
PC7: Travel Agencies / Airlines			0.001 (0.001, 0.001) $p < .001$	0.001 (0.001, 0.001) $p < .001$
PC8: Education			0.0001 (-0.0001, 0.0002) $p = .572$	0.00002 (-0.0002, 0.0002) $p = .866$
PC9: Repair Shops			0.0001 (0.00002, 0.0003) $p = .027$	0.0001 (0.000002, 0.0003) $p = .048$
PC10: Quasi Cash			0.0001 (-0.0001, 0.0002) $p = .243$	0.0001 (-0.0001, 0.0003) $p = .194$
<i>Demographics</i>				
Median house price (£'000,000s)				0.018 (0.013, 0.022) $p < .001$
Weekly income (£'000)				0.001 (-0.002, 0.004) $p = .431$
Proportion of free school meals (%)				0.00005 (0.000004, 0.0001) $p = .032$
(Intercept)	0.012 (0.011, 0.012) $p < .001$	0.009 (0.008, 0.010) $p < .001$	0.011 (0.010, 0.012) $p < .001$	0.006 (0.004, 0.008) $p < .001$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.002	.002	.002
Observations	1 371 580	1 371 580	1 371 580	1 371 580

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S5

Predicting whether an individual in the Argus dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.002 (0.001, 0.002) $p < .001$	0.001 (0.001, 0.002) $p < .001$	0.001 (0.001, 0.001) $p < .001$	0.001 (0.001, 0.001) $p < .001$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.0001 (-0.0002, -0.0001) $p < .001$	-0.0001 (-0.0002, -0.0001) $p < .001$	-0.0001 (-0.0002, -0.0001) $p < .001$
Month Spend (£'000s)		-0.003 (-0.004, -0.003) $p < .001$	-0.004 (-0.005, -0.003) $p < .001$	-0.004 (-0.005, -0.003) $p < .001$
Merchant APR (%)		0.0002 (0.0002, 0.0003) $p < .001$	0.0002 (0.0001, 0.0003) $p < .001$	0.0002 (0.0001, 0.0003) $p < .001$
Credit limit (£'000s)		0.0002 (0.0002, 0.0003) $p < .001$	0.0002 (0.0002, 0.0003) $p < .001$	0.0002 (0.0001, 0.0003) $p < .001$
Utilization (ending balance/ credit limit) (%)		0.0002 (0.0002, 0.0002) $p < .001$	0.0002 (0.0002, 0.0002) $p < .001$	0.0002 (0.0002, 0.0002) $p < .001$
<i>How individuals spend</i>				
PC1: Food Stores / Gas Stations			-0.001 (-0.002, -0.001) $p < .001$	-0.001 (-0.002, -0.001) $p < .001$
PC2: Department Stores / Clothing Stores			-0.00002 (-0.0004, 0.0003) $p = .902$	-0.0002 (-0.001, 0.0002) $p = .300$
PC3: Hotel/ Restaurants/ Other Transportation			0.001 (0.0005, 0.001) $p < .001$	0.001 (0.0003, 0.001) $p < .001$
PC4: Professional Services / Other Services			0.001 (0.0003, 0.001) $p = .001$	0.001 (0.0002, 0.001) $p = .005$
PC5: Interior Furnishing Stores			0.0002 (-0.0002, 0.001) $p = .284$	0.0002 (-0.0001, 0.001) $p = .255$
PC6: Sporting Goods/ Recreation			0.0002 (-0.00004, 0.0005) $p = .092$	0.0002 (-0.00002, 0.001) $p = .070$
PC7: Travel Agencies / Airlines			0.001 (0.0003, 0.001) $p < .001$	0.001 (0.0003, 0.001) $p < .001$
PC8: Education			0.0002 (-0.0001, 0.0004) $p = .141$	0.0001 (-0.0001, 0.0004) $p = .231$
PC9: Repair Shops			0.0001 (-0.0001, 0.0003) $p = .239$	0.0001 (-0.0001, 0.0002) $p = .320$
PC10: Quasi Cash			0.00005 (-0.0002, 0.0003) $p = .722$	0.0001 (-0.0002, 0.0003) $p = .668$
<i>Demographics</i>				
Median house price (£'000,000s)				0.017 (0.013, 0.022) $p < .001$
Weekly income (£'000)				-0.0001 (-0.003, 0.003) $p = .934$
Proportion of free school meals (%)				0.00003 (-0.00002, 0.0001) $p = .234$
(Intercept)	0.012 (0.012, 0.012) $p < .001$	0.006 (0.005, 0.007) $p < .001$	0.007 (0.005, 0.008) $p < .001$	0.003 (0.0002, 0.005) $p = .034$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.002	.003	.003
Observations	1 211 661	1 211 661	1 211 661	1 211 661

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S6

Predicting whether an individual in the Argus dataset missed payments in months $t = 1$ and $t = 2$ (0 = didn't miss payments; 1 = missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0001 (0.0001, 0.0002) $p < .001$	0.00003 (-0.00002, 0.0001) $p = .259$	-0.00001 (-0.0001, 0.0001) $p = .708$	-0.000005 (-0.0001, 0.0001) $p = .880$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.00001 (-0.00002, -0.00001) $p < .001$	-0.00001 (-0.00002, -0.00001) $p < .001$	-0.00001 (-0.00002, -0.00001) $p < .001$
Month Spend (£'000s)		-0.001 (-0.001, -0.001) $p < .001$	-0.001 (-0.001, -0.001) $p < .001$	-0.001 (-0.001, -0.001) $p < .001$
Merchant APR (%)		-0.000005 (-0.00002, 0.00001) $p = .629$	-0.00001 (-0.00002, 0.00001) $p = .589$	-0.00001 (-0.00002, 0.00001) $p = .574$
Credit limit (£'000s)		0.0001 (0.00005, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.00005, 0.0001) $p < .001$
Utilization (ending balance/ credit limit) (%)		0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$
<i>How individuals spend</i>				
PC1: Food Stores / Gas Stations			-0.0002 (-0.0003, -0.0001) $p < .001$	-0.0002 (-0.0002, -0.0001) $p = .001$
PC2: Department Stores / Clothing Stores			-0.0001 (-0.0001, 0.00001) $p = .073$	-0.0001 (-0.0002, -0.00001) $p = .033$
PC3: Hotel/ Restaurants/ Other Transportation			0.000001 (-0.0001, 0.0001) $p = .980$	-0.00001 (-0.0001, 0.0001) $p = .708$
PC4: Professional Services / Other Services			-0.00001 (-0.0001, 0.0001) $p = .861$	-0.00002 (-0.0001, 0.0001) $p = .711$
PC5: Interior Furnishing Stores			-0.00003 (-0.0001, 0.00005) $p = .505$	-0.00002 (-0.0001, 0.0001) $p = .528$
PC6: Sporting Goods/ Recreation			0.000001 (-0.0001, 0.0001) $p = .968$	0.000002 (-0.0001, 0.0001) $p = .933$
PC7: Travel Agencies / Airlines			0.00004 (-0.00002, 0.0001) $p = .215$	0.00004 (-0.00003, 0.0001) $p = .264$
PC8: Education			-0.00002 (-0.0001, 0.00001) $p = .142$	-0.00003 (-0.0001, 0.000005) $p = .098$
PC9: Repair Shops			-0.00001 (-0.00003, 0.000005) $p = .180$	-0.00001 (-0.00003, 0.000004) $p = .147$
PC10: Quasi Cash			0.00003 (-0.00003, 0.0001) $p = .303$	0.00003 (-0.00003, 0.0001) $p = .295$
<i>Demographics</i>				
Median house price (£'000,000s)				0.001 (-0.0001, 0.002) $p = .066$
Weekly income (£'000)				0.0003 (-0.0004, 0.001) $p = .410$
Proportion of free school meals (%)				0.00001 (-0.000002, 0.00002) $p = .108$
(Intercept)	0.001 (0.001, 0.001) $p < .001$	0.0001 (-0.0003, 0.0005) $p = .659$	0.00001 (-0.0004, 0.0004) $p = .971$	-0.001 (-0.001, 0.0001) $p = .082$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.003	.003	.003
Observations	1 291 999	1 291 999	1 291 999	1 291 999

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S7

Predicting whether an individual in the Argus dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0001 (0.0001, 0.0002) $p < .001$	0.00005 (-0.00002, 0.0001) $p = .149$	0.000002 (-0.0001, 0.0001) $p = .963$	0.00001 (-0.0001, 0.0001) $p = .782$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.00002 (-0.00002, -0.00001) $p < .001$	-0.00002 (-0.00002, -0.00001) $p < .001$	-0.00002 (-0.00002, -0.00001) $p < .001$
Month Spend (£'000s)		-0.001 (-0.001, -0.001) $p < .001$	-0.001 (-0.002, -0.001) $p < .001$	-0.001 (-0.002, -0.001) $p < .001$
Merchant APR (%)		0.000003 (-0.00002, 0.00002) $p = .780$	0.000002 (-0.00002, 0.00002) $p = .813$	0.000002 (-0.00002, 0.00002) $p = .835$
Credit limit (£'000s)		0.0001 (0.00005, 0.0001) $p < .001$	0.0001 (0.00005, 0.0001) $p < .001$	0.0001 (0.00004, 0.0001) $p < .001$
Utilization (ending balance/ credit limit) (%)		0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$
<i>How individuals spend</i>				
PC1: Food Stores / Gas Stations			-0.00003 (-0.0001, 0.0001) $p = .653$	-0.00002 (-0.0001, 0.0001) $p = .728$
PC2: Department Stores / Clothing Stores			0.00003 (-0.0001, 0.0001) $p = .509$	0.00001 (-0.0001, 0.0001) $p = .744$
PC3: Hotel/ Restaurants/ Other Transportation			0.0001 (0.00004, 0.0002) $p = .005$	0.0001 (0.00003, 0.0002) $p = .014$
PC4: Professional Services / Other Services			0.0001 (0.00002, 0.0002) $p = .025$	0.0001 (0.00001, 0.0002) $p = .038$
PC5: Interior Furnishing Stores			0.0001 (-0.00003, 0.0002) $p = .060$	0.0001 (-0.00002, 0.0002) $p = .055$
PC6: Sporting Goods/ Recreation			0.00002 (-0.00003, 0.0001) $p = .445$	0.00002 (-0.00003, 0.0001) $p = .417$
PC7: Travel Agencies / Airlines			0.0001 (0.00004, 0.0002) $p = .003$	0.0001 (0.00004, 0.0002) $p = .004$
PC8: Education			0.00003 (-0.00004, 0.0001) $p = .336$	0.00003 (-0.00004, 0.0001) $p = .392$
PC9: Repair Shops			-0.00001 (-0.00002, 0.00001) $p = .503$	-0.00001 (-0.00002, 0.00001) $p = .431$
PC10: Quasi Cash			-0.00001 (-0.00004, 0.00001) $p = .275$	-0.00001 (-0.00004, 0.00001) $p = .294$
<i>Demographics</i>				
Median house price (£'000,000s)				0.001 (-0.001, 0.003) $p = .171$
Weekly income (£'000)				0.0004 (-0.001, 0.001) $p = .456$
Proportion of free school meals (%)				0.00001 (-0.0000002, 0.000003) $p = .054$
(Intercept)	0.001 (0.001, 0.001) $p < .001$	-0.0002 (-0.001, 0.0002) $p = .387$	0.00002 (-0.0004, 0.0005) $p = .921$	-0.001 (-0.001, 0.0001) $p = .078$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.004	.004	.004
Observations	1 132 867	1 132 867	1 132 867	1 132 867

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S8

Predicting whether an individual in the Argus dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0004 (0.0003, 0.001) $p < .001$	0.0003 (0.0002, 0.0005) $p < .001$	0.0002 (0.0001, 0.0003) $p = .004$	0.0002 (0.0001, 0.0004) $p = .003$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.00004 (-0.0001, -0.00003) $p < .001$	-0.00004 (-0.0001, -0.00003) $p < .001$	-0.00004 (-0.0001, -0.00003) $p < .001$
Month Spend (£'000s)		-0.001 (-0.001, -0.001) $p < .001$	-0.001 (-0.002, -0.0005) $p = .002$	-0.001 (-0.002, -0.0005) $p = .002$
Merchant APR (%)		0.00003 (-0.000002, 0.0001) $p = .069$	0.00003 (-0.000005, 0.0001) $p = .089$	0.00003 (-0.00001, 0.0001) $p = .100$
Credit limit (£'000s)		0.00003 (-0.000002, 0.0001) $p = .063$	0.00004 (0.0000004, 0.0001) $p = .048$	0.00003 (-0.000001, 0.0001) $p = .059$
Utilization (ending balance/ credit limit) (%)		0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$
<i>How individuals spend</i>				
PC1: Department Stores / Clothing Stores			-0.0001 (-0.0003, 0.0002) $p = .601$	-0.0001 (-0.0003, 0.0002) $p = .520$
PC2: Food Stores / Gas Stations			-0.0004 (-0.001, -0.0002) $p = .002$	-0.0004 (-0.001, -0.0001) $p = .003$
PC3: Hotel/ Restaurants/ Other Transportation			0.00004 (-0.0002, 0.0003) $p = .793$	0.00002 (-0.0002, 0.0003) $p = .903$
PC4: Professional Services / Other Services			0.0002 (-0.00004, 0.0001) $p = .096$	0.0002 (-0.0001, 0.0001) $p = .115$
PC5: Interior Furnishing Stores			-0.00001 (-0.0002, 0.0002) $p = .924$	-0.00001 (-0.0002, 0.0002) $p = .948$
PC7: Travel Agencies / Airlines			-0.00001 (-0.0002, 0.0001) $p = .876$	-0.00001 (-0.0002, 0.0001) $p = .898$
PC6: Sporting Goods/ Recreation			0.0001 (-0.0001, 0.0003) $p = .296$	0.0001 (-0.0001, 0.0003) $p = .335$
PC8: Education			-0.000001 (-0.0002, 0.0002) $p = .988$	-0.000005 (-0.0002, 0.0002) $p = .954$
PC9: Quasi Cash			0.0001 (-0.0001, 0.0003) $p = .156$	0.0001 (-0.0001, 0.0003) $p = .154$
PC10: Repair Shops			0.00003 (-0.0001, 0.0001) $p = .491$	0.00003 (-0.0001, 0.0001) $p = .495$
<i>Demographics</i>				
Median house price (£'000,000s)				0.001 (-0.00005, 0.003) $p = .058$
Weekly income (£'000)				0.0002 (-0.001, 0.001) $p = .730$
Proportion of free school meals (%)				0.00004 (0.00001, 0.0001) $p = .003$
(Intercept)	0.003 (0.003, 0.003) $p < .001$	0.003 (0.003, 0.004) $p < .001$	0.003 (0.002, 0.004) $p < .001$	0.002 (0.001, 0.004) $p = .001$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.001	.001	.001
Observations	780 761	780 760	780 760	780 760

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S9

Predicting whether an individual in the Argus dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0005 (0.0003, 0.001) $p < .001$	0.0004 (0.0002, 0.001) $p < .001$	0.0003 (0.0001, 0.0004) $p = .001$	0.0003 (0.0001, 0.0004) $p < .001$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.00004 (-0.0001, -0.00002) $p < .001$	-0.00004 (-0.0001, -0.00002) $p < .001$	-0.00004 (-0.0001, -0.00002) $p < .001$
Month Spend (£'000s)		-0.001 (-0.001, -0.001) $p < .001$	-0.001 (-0.002, 0.0001) $p = .086$	-0.001 (-0.001, 0.0001) $p = .092$
Merchant APR (%)		0.0001 (0.00002, 0.0001) $p = .003$	0.0001 (0.00002, 0.0001) $p = .004$	0.0001 (0.00002, 0.0001) $p = .005$
Credit limit (£'000s)		0.00001 (-0.00003, 0.00005) $p = .597$	0.00001 (-0.00002, 0.0001) $p = .449$	0.00001 (-0.00003, 0.00005) $p = .559$
Utilization (ending balance/ credit limit) (%)		0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$	0.0001 (0.0001, 0.0001) $p < .001$
<i>How individuals spend</i>				
PC1: Department Stores / Clothing Stores			-0.0001 (-0.0004, 0.0002) $p = .577$	-0.0001 (-0.0004, 0.0002) $p = .483$
PC2: Food Stores / Gas Stations			-0.001 (-0.001, -0.0002) $p = .001$	-0.0005 (-0.001, -0.0002) $p = .002$
PC3: Hotel/ Restaurants/ Other Transportation			-0.0002 (-0.0005, 0.0001) $p = .201$	-0.0002 (-0.0005, 0.0001) $p = .145$
PC4: Professional Services / Other Services			0.0001 (-0.0002, 0.0004) $p = .597$	0.0001 (-0.0003, 0.0004) $p = .671$
PC5: Interior Furnishing Stores			-0.0001 (-0.0004, 0.0002) $p = .451$	-0.0001 (-0.0004, 0.0002) $p = .475$
PC7: Travel Agencies / Airlines			-0.0001 (-0.0003, 0.0001) $p = .287$	-0.0001 (-0.0003, 0.0001) $p = .299$
PC6: Sporting Goods/ Recreation			0.0001 (-0.0001, 0.0003) $p = .423$	0.0001 (-0.0001, 0.0003) $p = .471$
PC8: Education			-0.0001 (-0.0002, 0.0001) $p = .336$	-0.0001 (-0.0002, 0.0001) $p = .308$
PC9: Quasi Cash			0.0001 (-0.0001, 0.0003) $p = .393$	0.0001 (-0.0001, 0.0003) $p = .385$
PC10: Repair Shops			0.0002 (-0.0001, 0.001) $p = .225$	0.0002 (-0.0001, 0.001) $p = .226$
<i>Demographics</i>				
Median house price (£'000,000s)				0.002 (0.00001, 0.003) $p = .050$
Weekly income (£'000)				0.0005 (-0.001, 0.002) $p = .490$
Proportion of free school meals (%)				0.00004 (0.00001, 0.0001) $p = .004$
(Intercept)	0.003 (0.003, 0.003) $p < .001$	0.001 (0.0003, 0.002) $p = .010$	0.001 (-0.0003, 0.002) $p = .140$	-0.0004 (-0.002, 0.001) $p = .592$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.001	.002	.002
Observations	686 786	686 786	686 786	686 786

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S10

Predicting whether an individual in the Argus dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0001 (0.00002, 0.0001) $p = .005$	0.00003 (-0.00003, 0.0001) $p = .329$	0.00001 (-0.00004, 0.0001) $p = .699$	0.00001 (-0.00004, 0.0001) $p = .679$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.000001 (-0.00001, 0.000004) $p = .723$	-0.000001 (-0.00001, 0.000004) $p = .687$	-0.000001 (-0.00001, 0.000004) $p = .738$
Month Spend (£'000s)		-0.001 (-0.001, -0.0004) $p < .001$	-0.001 (-0.001, -0.0004) $p < .001$	-0.001 (-0.001, -0.0004) $p < .001$
Merchant APR (%)		0.00001 (-0.00001, 0.00002) $p = .437$	0.00001 (-0.00001, 0.00002) $p = .456$	0.00001 (-0.00001, 0.00002) $p = .469$
Credit limit (£'000s)		0.00004 (0.00002, 0.0001) $p < .001$	0.00004 (0.00002, 0.0001) $p < .001$	0.00004 (0.00002, 0.0001) $p < .001$
Utilization (ending balance/ credit limit) (%)		0.00003 (0.00003, 0.00004) $p < .001$	0.00003 (0.00003, 0.00004) $p < .001$	0.00003 (0.00003, 0.00004) $p < .001$
<i>How individuals spend</i>				
PC1: Department Stores / Clothing Stores			0.00003 (-0.00005, 0.0001) $p = .420$	0.00003 (-0.00005, 0.0001) $p = .414$
PC2: Food Stores / Gas Stations			-0.00001 (-0.0001, 0.0001) $p = .779$	-0.00001 (-0.0001, 0.0001) $p = .800$
PC3: Hotel/ Restaurants/ Other Transportation			0.00002 (-0.0001, 0.0001) $p = .552$	0.00002 (-0.0001, 0.0001) $p = .536$
PC4: Professional Services / Other Services			0.0001 (-0.00004, 0.0002) $p = .175$	0.0001 (-0.00004, 0.0002) $p = .174$
PC5: Interior Furnishing Stores			0.0001 (-0.00003, 0.0001) $p = .206$	0.0001 (-0.00003, 0.0001) $p = .214$
PC7: Travel Agencies / Airlines			0.00001 (-0.00004, 0.0001) $p = .653$	0.00001 (-0.00004, 0.0001) $p = .651$
PC6: Sporting Goods/ Recreation			0.00002 (-0.00004, 0.0001) $p = .565$	0.00002 (-0.00004, 0.0001) $p = .585$
PC8: Education			0.00001 (-0.00003, 0.00004) $p = .622$	0.00001 (-0.00003, 0.00004) $p = .621$
PC9: Quasi Cash			0.000002 (-0.00002, 0.00002) $p = .842$	0.000002 (-0.00002, 0.00002) $p = .853$
PC10: Repair Shops			-0.000001 (-0.00002, 0.00001) $p = .884$	-0.000001 (-0.00002, 0.00001) $p = .887$
<i>Demographics</i>				
Median house price (£'000,000s)				0.0002 (-0.0004, 0.001) $p = .543$
Weekly income (£'000)				-0.0002 (-0.001, 0.0002) $p = .290$
Proportion of free school meals (%)				0.000004 (-0.000005, 0.00001) $p = .345$
(Intercept)	0.0004 (0.0003, 0.0004) $p < .001$	-0.0002 (-0.001, 0.0002) $p = .295$	-0.0001 (-0.0005, 0.0003) $p = .665$	0.00001 (-0.001, 0.001) $p = .966$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.001	.001	.001
Observations	733 937	733 936	733 936	733 936

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S11

Predicting whether an individual in the Argus dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by MC (£'000s) (3), and demographics (4).

Independent variable	(1)	(2)	(3)	(4)
Entropy (6 months)	0.0001 (0.00003, 0.0001) $p = .004$	0.00004 (-0.00002, 0.0001) $p = .180$	0.00003 (-0.00004, 0.0001) $p = .395$	0.00003 (-0.00003, 0.0001) $p = .347$
Control variables				
<i>Account Characteristics</i>				
Account Tenure (years)		-0.000004 (-0.00001, 0.000001) $p = .147$	-0.000004 (-0.00001, 0.000001) $p = .145$	-0.000004 (-0.00001, 0.000002) $p = .184$
Month Spend (£'000s)		-0.00005 (-0.001, -0.0004) $p < .001$	-0.001 (-0.001, -0.0002) $p = .002$	-0.001 (-0.001, -0.0002) $p = .002$
Merchant APR (%)		0.00003 (0.00002, 0.00004) $p < .001$	0.00003 (0.00002, 0.00004) $p < .001$	0.00003 (0.00002, 0.00004) $p < .001$
Credit limit (£'000s)		0.00003 (0.00002, 0.0001) $p < .001$	0.00003 (0.00002, 0.0001) $p < .001$	0.00003 (0.00002, 0.0001) $p < .001$
Utilization (ending balance/ credit limit) (%)		0.00004 (0.00003, 0.00004) $p < .001$	0.00004 (0.00003, 0.00004) $p < .001$	0.00004 (0.00003, 0.00004) $p < .001$
<i>How individuals spend</i>				
PC1: Department Stores / Clothing Stores			0.00003 (-0.0001, 0.0001) $p = .533$	0.00003 (-0.0001, 0.0001) $p = .554$
PC2: Food Stores / Gas Stations			-0.00005 (-0.0002, 0.0001) $p = .463$	-0.00004 (-0.0002, 0.0001) $p = .525$
PC3: Hotel/ Restaurants/ Other Transportation			0.00001 (-0.0001, 0.0001) $p = .817$	0.00001 (-0.0001, 0.0001) $p = .841$
PC4: Professional Services / Other Services			0.00004 (-0.0001, 0.0002) $p = .626$	0.00003 (-0.0001, 0.0002) $p = .638$
PC5: Interior Furnishing Stores			0.00004 (-0.0001, 0.0001) $p = .521$	0.00004 (-0.0001, 0.0001) $p = .521$
PC7: Travel Agencies / Airlines			0.000003 (-0.0001, 0.0001) $p = .929$	0.000003 (-0.0001, 0.0001) $p = .920$
PC6: Sporting Goods/ Recreation			0.000003 (-0.0001, 0.0001) $p = .953$	0.000001 (-0.0001, 0.0001) $p = .987$
PC8: Education			0.00002 (-0.00003, 0.0001) $p = .423$	0.00002 (-0.00003, 0.0001) $p = .437$
PC9: Quasi Cash			-0.00001 (-0.00004, 0.00003) $p = .696$	-0.00001 (-0.00004, 0.00003) $p = .696$
PC10: Repair Shops			-0.000003 (-0.00002, 0.00001) $p = .678$	-0.000003 (-0.00002, 0.00001) $p = .687$
<i>Demographics</i>				
Median house price (£'000,000s)				0.0002 (-0.0004, 0.001) $p = .500$
Weekly income (£'000)				-0.0001 (-0.001, 0.0004) $p = .791$
Proportion of free school meals (%)				0.00001 (0.0000001, 0.00002) $p = .047$
(Intercept)	0.0004 (0.0004, 0.0005) $p < .001$	-0.001 (-0.001, -0.0004) $p < .001$	-0.001 (-0.001, -0.0003) $p = .002$	-0.001 (-0.001, -0.0002) $p = .005$
Customer fixed-effects	No	No	No	No
Month fixed-effects	No	Yes	Yes	Yes
R^2	.000	.002	.002	.002
Observations	640 499	640 499	640 499	640 499

Note: Independent variable of interest is the Standardised Entropy for spending patterns in the past 6 months. SE clustered at account level.

Supplementary Table S12

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	-.00033 (-.00079, .00012) $p = .152$	-.00034 (-.00080, .00011) $p = .141$	-.00063 (-.0011, -.00014) $p = .011$	-.00032 (-.00081, .00016) $p = .189$	-.00032 (-.00082, .00018) $p = .206$
Control variables					
<i>What individuals spend</i>					
Month spend		-.000080 (-.00021, .000057) $p = .252$			
Communication			.022 (.016, .027) $p < .001$	.017 (.011, .022) $p < .001$	.016 (.010, .022) $p < .001$
Financial services			.000023 (-.00019, .00023) $p = .827$	-.0034 (-.0039, -.0028) $p < .001$	-.0035 (-.0041, -.0029) $p < .001$
Hobbies			.00012 (-.00025, .00050) $p = .527$	-.0028 (-.0034, -.0022) $p < .001$	-.0030 (-.0036, -.0024) $p < .001$
Household bills			-.0040 (-.0064, -.0017) $p < .001$	-.0068 (-.0092, -.0045) $p < .001$	-.0063 (-.0087, -.0038) $p < .001$
Miscellaneous			.00029 (-.0018, .0024) $p = .789$	-.0026 (-.0048, -.00045) $p = .017$	-.0027 (-.0049, -.00058) $p = .013$
Motor			-.00040 (-.00095, .00014) $p = .149$	-.0035 (-.0042, -.0027) $p < .001$	-.0037 (-.0044, -.0029) $p < .001$
Retail			-.0011 (-.0017, -.00061) $p < .001$	-.0026 (-.0032, -.0020) $p < .001$	-.0029 (-.0035, -.0022) $p < .001$
Services			.00016 (-.00074, .0010) $p = .717$	-.0021 (-.0031, -.0012) $p < .001$	-.0022 (-.0032, -.0012) $p < .001$
Travel			-.0011 (-.0017, -.00050) $p < .001$	-.0030 (-.0037, -.0024) $p < .001$	-.0032 (-.0039, -.0025) $p < .001$
Other			.0023 (.0011, .0035) $p < .001$	-.0035 (-.0064, -.00075) $p = .013$	-.0037 (-.0066, -.00095) $p = .008$
<i>How individuals spend</i>					
ATM				.0059 (.0028, .0090) $p < .001$	.0063 (.0032, .0095) $p < .001$
Direct debit				.0035 (.0028, .0041) $p < .001$	.0036 (.0030, .0043) $p < .001$
Debit card				.0035 (.0029, .0040) $p < .001$	.0037 (.0031, .0042) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00086 (-.0017, .000067) $p = .069$
Age					-.000063 (-.000095, -.000030) $p < .001$
Annual income (£'000s)					-.0000013 (-.0000077, .0000049) $p = .665$
(Intercept)	.0085 (.0080, .0089) $p < .001$	.0087 (.0081, .0093) $p < .001$	.0079 (.0071, .0087) $p < .001$	.0077 (.0069, .0085) $p < .001$	.010 (.0091, .012) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.002	.002
Observations	163 892	163 892	163 892	163 892	161 855

Supplementary Table S13

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	-.00045 (-.0010, .00017) $p = .158$	-.00045 (-.0010, .00017) $p = .158$	-.00087 (-.0015, -.00020) $p = .010$	-.00045 (-.0011, .00021) $p = .182$	-.00030 (-.00099, .00040) $p = .400$
Control variables					
<i>What individuals spend</i>					
Month spend		-.0000030 (-.00019, .00018) $p = .974$			
Communication			.036 (.028, .044) $p < .001$	.029 (.021, .037) $p < .001$	.029 (.021, .037) $p < .001$
Financial services			.000047 (-.00024, .00033) $p = .746$	-.0046 (-.0054, -.0038) $p < .001$	-.0048 (-.0056, -.0040) $p < .001$
Hobbies			.00050 (-.000018, .0010) $p = .058$	-.0037 (-.0046, -.0029) $p < .001$	-.0039 (-.0047, -.0031) $p < .001$
Household bills			-.0044 (-.0076, -.0013) $p = .005$	-.0080 (-.011, -.0048) $p < .001$	-.0068 (-.010, -.0035) $p < .001$
Miscellaneous			-.0010 (-.0039, .0018) $p = .483$	-.0050 (-.0080, -.0021) $p < .001$	-.0051 (-.0081, -.0021) $p < .001$
Motor			.00015 (-.00060, .00091) $p = .689$	-.0043 (-.0053, -.0033) $p < .001$	-.0044 (-.0055, -.0034) $p < .001$
Retail			-.0017 (-.0025, -.00097) $p < .001$	-.0038 (-.0047, -.0030) $p < .001$	-.0038 (-.0047, -.0030) $p < .001$
Services			-.00036 (-.0016, .00089) $p = .574$	-.0035 (-.0049, -.0022) $p < .001$	-.0037 (-.0051, -.0024) $p < .001$
Travel			-.0014 (-.0023, -.00066) $p < .001$	-.0044 (-.0053, -.0034) $p < .001$	-.0045 (-.0054, -.0035) $p < .001$
Other			.0029 (.0013, .0046) $p < .001$	-.0052 (-.0089, -.0015) $p = .004$	-.0053 (-.0090, -.0017) $p = .004$
<i>How individuals spend</i>					
ATM				.0082 (.0041, .012) $p < .001$	.0088 (.0047, .012) $p < .001$
Direct debit				.0047 (.0038, .0055) $p < .001$	.0048 (.0040, .0057) $p < .001$
Debit card				.0050 (.0043, .0057) $p < .001$	.0052 (.0045, .0059) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.0018 (-.0030, -.00053) $p = .005$
Age					-.00012 (-.00016, -.000076) $p < .001$
Annual income (£'000s)					.0000039 (-.0000047, .000012) $p = .374$
(Intercept)	.013 (.013, .014) $p < .001$	.013 (.013, .014) $p < .001$	.012 (.011, .013) $p < .001$	.012 (.011, .013) $p < .001$	.018 (.015, .020) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.002	.003
Observations	141 190	141 190	141 190	141 190	139 416

Supplementary Table S14

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ (0 = didn't miss payments; 1 = missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	-.000091 (-.00030, .00012) $p = .404$	-.000087 (-.00030, .00012) $p = .423$	-.00022 (-.00045, .000059) $p = .056$	-.00013 (-.00037, .000094) $p = .243$	-.00010 (-.00034, .00013) $p = .394$
Control variables					
<i>What individuals spend</i>					
Month spend		.000025 (-.000041, .000092) $p = .458$			
Communication			.0069 (.0046, .0091) $p < .001$	.0055 (.0032, .0078) $p < .001$	.0055 (.0032, .0078) $p < .001$
Financial services			.000031 (-.000072, .00013) $p = .550$	-.0010 (-.0013, -.00070) $p < .001$	-.0010 (-.0013, -.00071) $p < .001$
Hobbies			.00017 (.000015, .00033) $p = .031$	-.00076 (-.0010, -.00047) $p < .001$	-.00076 (-.0010, -.00047) $p < .001$
Household bills			-.0015 (-.0026, -.00043) $p = .006$	-.0024 (-.0035, -.0012) $p < .001$	-.0020 (-.0032, -.00089) $p < .001$
Miscellaneous			.000088 (-.00082, .00099) $p = .848$	-.00094 (-.0018, .000022) $p = .050$	-.00094 (-.0018, .000044) $p = .051$
Motor			-.000098 (-.00039, .00019) $p = .511$	-.0010 (-.0014, -.00069) $p < .001$	-.0010 (-.0014, -.00069) $p < .001$
Retail			-.00047 (-.00074, -.00019) $p < .001$	-.00093 (-.0012, -.00064) $p < .001$	-.00089 (-.0011, -.00059) $p < .001$
Services			-.00012 (-.00055, .00029) $p = .553$	-.00090 (-.0013, -.00043) $p < .001$	-.00087 (-.0013, -.00040) $p < .001$
Travel			-.00035 (-.00075, .000038) $p = .077$	-.00064 (-.0010, -.00023) $p = .001$	-.00062 (-.0010, -.00022) $p = .002$
Other			.0014 (.00080, .0020) $p < .001$	-.0024 (-.0059, .0010) $p = .172$	-.0023 (-.0058, .0011) $p = .191$
<i>How individuals spend</i>					
ATM				.0037 (.00025, .0073) $p = .035$	.0037 (.00021, .0073) $p = .037$
Direct debit				.0010 (.00071, .0013) $p < .001$	.0010 (.00072, .0013) $p < .001$
Debit card				.0011 (.00083, .0013) $p < .001$	.0011 (.00083, .0013) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00019 (-.00063, .00024) $p = .390$
Age					-.000017 (-.000032, -.0000024) $p = .022$
Annual income (£'000s)					.0000019 (-.00000099, .0000048) $p = .195$
(Intercept)	.0017 (.0015, .0019) $p < .001$	.0016 (.0013, .0019) $p < .001$	.0014 (.0010, .0018) $p < .001$	.0013 (.0010, .0017) $p < .001$	.0022 (.0014, .0029) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.001
Observations	149 493	149 493	149 493	149 493	149 493

Supplementary Table S15

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ (0 = didn't miss payments; 1 = missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	-.00025 (-.00047, -.000039) $p = .020$	-.00025 (-.00047, -.000034) $p = .023$	-.00037 (-.00060, -.00013) $p = .002$	-.00031 (-.00054, -.000075) $p = .009$	-.00030 (-.00054, -.000062) $p = .014$
Control variables					
<i>What individuals spend</i>					
Month spend		.000032 (-.000035, .00010) $p = .347$			
Communication			.020 (.017, .022) $p < .001$	.019 (.017, .021) $p < .001$	.019 (.017, .021) $p < .001$
Financial services			.0000013 (-.00010, .00010) $p = .979$	-.00067 (-.00098, -.00036) $p < .001$	-.00066 (-.00097, -.00035) $p < .001$
Hobbies			.00012 (-.00038, .00029) $p = .132$	-.00057 (-.00086, -.00027) $p < .001$	-.00056 (-.00086, -.00027) $p < .001$
Household bills			-.0032 (-.0043, -.0020) $p < .001$	-.0036 (-.0048, -.0024) $p < .001$	-.0035 (-.0047, -.0023) $p < .001$
Miscellaneous			.00015 (-.00077, .0010) $p = .747$	-.00055 (-.0015, .00040) $p = .258$	-.00054 (-.0015, .00042) $p = .270$
Motor			-.00019 (-.00049, .00010) $p = .210$	-.00092 (-.0013, -.00053) $p < .001$	-.00091 (-.0013, -.00052) $p < .001$
Retail			-.00048 (-.00076, -.00020) $p < .001$	-.00082 (-.0011, -.00052) $p < .001$	-.00079 (-.0010, -.00048) $p < .001$
Services			-.00032 (-.00075, .00010) $p = .143$	-.00089 (-.0013, -.00041) $p < .001$	-.00086 (-.0013, -.00038) $p < .001$
Travel			-.00044 (-.00084, -.000040) $p = .030$	-.00065 (-.0010, -.00023) $p = .001$	-.00063 (-.0010, -.00022) $p = .002$
Other			.0013 (.00071, .0019) $p < .001$	-.0016 (-.0051, .0019) $p = .365$	-.0015 (-.0050, .0020) $p = .404$
<i>How individuals spend</i>					
ATM				.0029 (-.00067, .0065) $p = .110$	.0028 (-.00080, .0064) $p = .127$
Direct debit				.00059 (.00025, .00093) $p < .001$	.00059 (.00025, .00093) $p < .001$
Debit card				.00082 (.00054, .0011) $p < .001$	.00082 (.00054, .0010) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00011 (-.00056, .00033) $p = .618$
Age					-.0000029 (-.000018, .000012) $p = .708$
Annual income (£'000s)					.0000013 (-.0000015, .0000043) $p = .362$
(Intercept)	.0017 (.0015, .0020) $p < .001$	.0017 (.0014, .0019) $p < .001$	.00075 (.00036, .0011) $p < .001$	.00068 (.00030, .0010) $p < .001$	.00089 (.00010, .0016) $p = .025$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.002	.003	.003
Observations	149 489	149 489	149 489	149 489	149 489

Supplementary Table S16

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0010 (.00055, .0015) $p < .001$	.0010 (.00054, .0015) $p < .001$	.0010 (.00051, .0015) $p < .001$	.0012 (.00072, .0017) $p < .001$	.0015 (.00093, .0020) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.000079 (-.00019, .000032) $p = .164$			
Communication			.0063 (.0020, .010) $p = .003$	.0036 (-.00074, .0080) $p = .103$	.0083 (.0024, .014) $p = .005$
Financial services			-.000068 (-.00021, .000074) $p = .348$	-.0019 (-.0025, -.0013) $p < .001$	-.0019 (-.0025, -.0013) $p < .001$
Hobbies			.00084 (.000058, .0016) $p = .035$	-.00091 (-.0018, .000014) $p = .053$	-.00093 (-.0018, .000013) $p = .053$
Household bills			-.0023 (-.0042, -.00034) $p = .021$	-.0038 (-.0058, -.0017) $p < .001$	-.0034 (-.0055, -.0012) $p = .002$
Miscellaneous			-.00018 (-.0012, .00088) $p = .732$	-.0020 (-.0032, -.00087) $p < .001$	-.0019 (-.0032, -.00070) $p = .002$
Motor			-.00072 (-.0013, -.00010) $p = .021$	-.0025 (-.0032, -.0017) $p < .001$	-.0025 (-.0033, -.0016) $p < .001$
Retail			-.00028 (-.00083, .00027) $p = .317$	-.0012 (-.0018, -.00060) $p < .001$	-.0013 (-.0019, -.00072) $p < .001$
Services			-.00096 (-.0019, -.000035) $p = .041$	-.0020 (-.0030, -.0010) $p < .001$	-.0021 (-.0031, -.0011) $p < .001$
Travel			-.00052 (-.0012, .00017) $p = .140$	-.00072 (-.0014, -.000017) $p = .044$	-.00078 (-.0014, -.000072) $p = .030$
Other			.0044 (.0030, .0059) $p < .001$	-.0012 (-.0064, .0038) $p = .625$	-.0016 (-.0068, .0036) $p = .545$
<i>How individuals spend</i>					
ATM				.0057 (.00034, .011) $p = .036$	.0064 (.00098, .011) $p = .020$
Direct debit				.0018 (.0012, .0024) $p < .001$	.0017 (.0011, .0024) $p < .001$
Debit card				.0019 (.0013, .0024) $p < .001$	.0019 (.0013, .0024) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					.00070 (-.00027, .0016) $p = .159$
Age					-.00011 (-.00014, -.000076) $p < .001$
Annual income (£'000s)					-.0000060 (-.0000099, -.0000021) $p = .002$
(Intercept)	.0058 (.0053, .0062) $p < .001$	.0060 (.0054, .0066) $p < .001$	.0052 (.0044, .0060) $p < .001$	.0049 (.0041, .0057) $p < .001$	.0089 (.0072, .010) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.002
Observations	100 257	100 257	100 257	100 257	98 831

Supplementary Table S17

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0012 (.00058, .0019) $p < .001$	.0012 (.00058, .0019) $p < .001$	.0010 (.00035, .0017) $p = .003$	.0012 (.00055, .0019) $p < .001$	.0016 (.00090, .0024) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.00027 (-.00042, -.00011) $p < .001$			
Communication			.015 (.0097, .021) $p < .001$	.013 (.0075, .019) $p < .001$	.027 (.019, .035) $p < .001$
Financial services			-.00022 (-.00042, -.000037) $p = .019$	-.0017 (-.0025, -.00097) $p < .001$	-.0017 (-.0026, -.00093) $p < .001$
Hobbies			.0022 (.0012, .0033) $p < .001$	.00078 (-.00049, .0020) $p = .229$	.00085 (-.00043, .0021) $p = .195$
Household bills			-.0076 (-.010, -.0048) $p < .001$	-.0085 (-.011, -.0056) $p < .001$	-.0069 (-.010, -.0038) $p < .001$
Miscellaneous			-.00058 (-.0020, .00086) $p = .430$	-.0021 (-.0037, -.00051) $p = .009$	-.0018 (-.0036, -.00011) $p = .036$
Motor			-.00067 (-.0015, .00016) $p = .115$	-.0021 (-.0032, -.0010) $p < .001$	-.0021 (-.0032, -.0010) $p < .001$
Retail			-.0012 (-.0020, -.00050) $p = .001$	-.0020 (-.0028, -.0011) $p < .001$	-.0021 (-.0029, -.0012) $p < .001$
Services			-.00061 (-.0018, .00063) $p = .333$	-.0014 (-.0027, -.000089) $p = .036$	-.0013 (-.0026, .000049) $p = .058$
Travel			-.00087 (-.0018, .000084) $p = .074$	-.0010 (-.0020, -.000088) $p = .032$	-.0011 (-.0021, -.000016) $p = .021$
Other			.0052 (.0031, .0073) $p < .001$	-.00069 (-.0099, .0085) $p = .882$	-.0013 (-.010, .0079) $p = .782$
<i>How individuals spend</i>					
ATM				.0059 (-.0035, .015) $p = .218$	.0071 (-.0024, .016) $p = .142$
Direct debit				.0013 (.00050, .0022) $p = .001$	.0013 (.00045, .0022) $p = .003$
Debit card				.0016 (.00087, .0024) $p < .001$	.0015 (.00077, .0023) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					.00031 (-.0010, .0016) $p = .654$
Age					-.00020 (-.00025, -.00015) $p < .001$
Annual income (£'000s)					-.000000067 (-.0000053, .0000052) $p = .980$
(Intercept)	.0095 (.0088, .010) $p < .001$	.010 (.0095, .011) $p < .001$	.0098 (.0087, .010) $p < .001$	.0095 (.0084, .010) $p < .001$	.017 (.014, .019) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.002	.002	.003
Observations	85 458	85 458	85 458	85 458	84 228

Supplementary Table S18

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ (0 = didn't miss payments; 1 = missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00017 (.000024, .00032) $p = .022$	.00017 (.000023, .00032) $p = .023$	.00015 (-.0000074, .00031) $p = .061$	.00016 (.00000011, .00032) $p = .049$	.00019 (.000029, .00036) $p = .021$
Control variables					
<i>What individuals spend</i>					
Month spend		-.000022 (-.000057, .000012) $p = .212$			
Communication			.00059 (-.00075, .0019) $p = .386$	.00052 (-.00086, .0019) $p = .461$	.00055 (-.00083, .0019) $p = .436$
Financial services			-.0000018 (-.000046, .000042) $p = .933$	-.000069 (-.00025, .00011) $p = .452$	-.000068 (-.00024, .00011) $p = .462$
Hobbies			-.000096 (-.00034, .00015) $p = .445$	-.00017 (-.00046, .00012) $p = .256$	-.00017 (-.00046, .00012) $p = .259$
Household bills			-.00053 (-.0011, .000086) $p = .091$	-.00054 (-.0012, .00010) $p = .100$	-.00037 (-.0010, .00029) $p = .273$
Miscellaneous			-.000028 (-.00043, .00037) $p = .887$	-.000099 (-.00053, .00033) $p = .654$	-.000097 (-.00053, .00033) $p = .662$
Motor			-.000079 (-.00028, .00012) $p = .435$	-.00015 (-.00041, .00010) $p = .240$	-.00015 (-.00040, .00010) $p = .255$
Retail			-.000087 (-.00026, .000086) $p = .325$	-.00012 (-.00032, .000070) $p = .208$	-.00012 (-.00032, .000075) $p = .223$
Services			-.00012 (-.00043, .00017) $p = .406$	-.00015 (-.00047, .00016) $p = .330$	-.00015 (-.00047, .00016) $p = .342$
Travel			-.000097 (-.00033, .00013) $p = .421$	-.000094 (-.00033, .00014) $p = .438$	-.00010 (-.00033, .00013) $p = .404$
Other			.00051 (.000066, .00096) $p = .024$	-.00010 (-.0016, .0014) $p = .896$	-.00013 (-.0016, .0014) $p = .868$
<i>How individuals spend</i>					
ATM				.00065 (-.00095, .0022) $p = .426$	.00077 (-.00084, .0023) $p = .350$
Direct debit				.000044 (-.00015, .00024) $p = .660$	.000046 (-.00015, .00024) $p = .647$
Debit card				.000081 (-.000095, .00025) $p = .367$	.000080 (-.000096, .00025) $p = .373$
<i>Demographics</i>					
Gender (0 = Male)					.000043 (-.00026, .00035) $p = .783$
Age					-.000014 (-.000025, -.0000040) $p = .007$
Annual income (£'000s)					-.000000010 (-.0000012, .0000011) $p = .985$
(Intercept)	.00053 (.00038, .00068) $p < .001$	.00060 (.00041, .00079) $p < .001$	.00059 (.00034, .00084) $p < .001$	.00058 (.00033, .00084) $p < .001$	.0011 (.00064, .0017) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.000	.000	.000
Observations	91 526	91 526	91 526	91 526	91 526

Supplementary Table S19

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ (0 = didn't miss payments; 1 = missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00035 (.00015, .00055) $p < .001$	.00035 (.00015, .00055) $p < .001$	.00050 (.00028, .00071) $p < .001$	.00050 (.00028, .00072) $p < .001$	.00049 (.00027, .00071) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		.000052 (.0000056, .000099) $p = .027$			
Communication			-.00011 (-.0019, .0017) $p = .903$	-.00038 (-.0022, .0014) $p = .681$	-.00036 (-.0022, .0014) $p = .701$
Financial services			-.0000090 (-.000068, .000050) $p = .765$	-.00021 (-.00046, .000023) $p = .076$	-.00021 (-.00045, .000026) $p = .081$
Hobbies			-.00014 (-.00047, .00018) $p = .378$	-.00038 (-.00078, .0000067) $p = .054$	-.00038 (-.00078, .000012) $p = .057$
Household bills			-.00093 (-.0017, -.00010) $p = .027$	-.0011 (-.0019, -.00025) $p = .011$	-.0011 (-.0020, -.00027) $p = .010$
Miscellaneous			.00040 (-.00013, .00093) $p = .140$	.00019 (-.00038, .00077) $p = .513$	.00020 (-.00038, .00078) $p = .494$
Motor			-.000095 (-.00036, .00017) $p = .483$	-.00031 (-.00065, .000031) $p = .075$	-.00030 (-.00065, .000037) $p = .080$
Retail			.00049 (.00026, .00072) $p < .001$	.00033 (.000076, .00060) $p = .011$	.00035 (.000085, .00061) $p = .009$
Services			.00021 (-.00019, .00061) $p = .311$	.00010 (-.00032, .00052) $p = .633$	.00011 (-.00031, .00053) $p = .608$
Travel			-.00012 (-.00044, .00019) $p = .440$	-.00021 (-.00053, .00010) $p = .180$	-.00020 (-.00052, .00010) $p = .198$
Other			.0017 (.0011, .0023) $p < .001$	.013 (.011, .015) $p < .001$	.013 (.011, .015) $p < .001$
<i>How individuals spend</i>					
ATM				-.013 (-.015, -.010) $p < .001$	-.013 (-.015, -.011) $p < .001$
Direct debit				.00014 (-.00012, .00040) $p = .296$	.00014 (-.00012, .00040) $p = .292$
Debit card				.00025 (.000023, .00049) $p = .031$	.00025 (.000021, .00049) $p = .032$
<i>Demographics</i>					
Gender (0 = Male)					.000056 (-.00035, .00046) $p = .787$
Age					.0000079 (-.0000067, .000022) $p = .289$
Annual income (£'000s)					.00000035 (-.0000012, .0000019) $p = .664$
(Intercept)	.00095 (.00075, .0011) $p < .001$	.00079 (.00054, .0010) $p < .001$	.00027 (-.000058, .00061) $p = .105$	.00051 (.00017, .00085) $p = .002$	.00017 (-.00054, .00089) $p = .639$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.003	.003
Observations	91 526	91 526	91 526	91 526	91 526

Supplementary Table S20

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00034 (.00022, .00047) $p < .001$	.00034 (.00022, .00047) $p < .001$	.00021 (.000081, .00035) $p = .001$	.00024 (.00010, .00037) $p < .001$	.00036 (.00022, .00049) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		.0000065 (-.000036, .000049) $p = .764$			
Communication			.011 (.010, .012) $p < .001$	.010 (.0090, .012) $p < .001$	.012 (.010, .013) $p < .001$
Financial services			-.0000074 (-.000065, .000050) $p = .800$	-.00078 (-.0010, -.00050) $p < .001$	-.00073 (-.0010, -.00044) $p < .001$
Hobbies			.00048 (.00033, .00064) $p < .001$	-.00026 (-.00056, .000045) $p = .094$	-.00023 (-.00054, .000073) $p = .135$
Household bills			-.0022 (-.0028, -.0016) $p < .001$	-.0029 (-.0036, -.0022) $p < .001$	-.0018 (-.0025, -.0010) $p < .001$
Miscellaneous			.00010 (-.00028, .00049) $p = .606$	-.00067 (-.0011, -.00019) $p = .005$	-.00055 (-.0010, -.000066) $p = .026$
Motor			-.00020 (-.00040, .00000018) $p = .050$	-.00094 (-.0012, -.00061) $p < .001$	-.00089 (-.0012, -.00056) $p < .001$
Retail			-.00064 (-.00085, -.00043) $p < .001$	-.0012 (-.0015, -.00096) $p < .001$	-.0011 (-.0014, -.00080) $p < .001$
Services			-.00023 (-.00056, .00010) $p = .179$	-.00091 (-.0013, -.00050) $p < .001$	-.00081 (-.0012, -.00039) $p < .001$
Travel			-.00049 (-.00079, -.00018) $p = .001$	-.00097 (-.0013, -.00062) $p < .001$	-.00099 (-.0013, -.00063) $p < .001$
Other			.0011 (.00077, .0014) $p < .001$	-.00069 (-.0028, .0014) $p = .521$	-.00076 (-.0029, .0013) $p = .483$
<i>How individuals spend</i>					
ATM				.0018 (-.00034, .0039) $p = .099$	.0020 (-.00012, .0042) $p = .064$
Direct debit				.00078 (.00047, .0010) $p < .001$	.00073 (.00042, .0010) $p < .001$
Debit card				.00077 (.00050, .0010) $p < .001$	.00072 (.00045, .0010) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00059 (-.00085, -.00034) $p < .001$
Age					-.000070 (-.000078, -.000061) $p < .001$
Annual income (£'000s)					.0000012 (-.0000060, .0000031) $p = .182$
(Intercept)	.0027 (.0026, .0028) $p < .001$	.0027 (.0025, .0028) $p < .001$	.0023 (.0021, .0025) $p < .001$	.0022 (.0020, .0025) $p < .001$	.0052 (.0048, .0056) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.001
Observations	666 918	666 918	666 918	666 918	660 729

Supplementary Table S21

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00043 (.00027, .00058) $p < .001$	.00043 (.00028, .00059) $p < .001$	.00025 (.000089, .00042) $p = .002$	.00029 (.00012, .00046) $p < .001$	.00046 (.00029, .00062) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		.000029 (-.000022, .000082) $p = .263$			
Communication			.015 (.013, .017) $p < .001$	.014 (.012, .016) $p < .001$	.017 (.015, .019) $p < .001$
Financial services			-.000020 (-.000090, .000048) $p = .557$	-.0010 (-.0014, -.00073) $p < .001$	-.00099 (-.0013, -.00064) $p < .001$
Hobbies			.00083 (.00063, .0010) $p < .001$	-.00021 (-.00059, .00016) $p = .269$	-.00015 (-.00054, .00022) $p = .418$
Household bills			-.0026 (-.0034, -.0018) $p < .001$	-.0035 (-.0043, -.0027) $p < .001$	-.0019 (-.0028, -.0011) $p < .001$
Miscellaneous			.000027 (-.00044, .00049) $p = .907$	-.0010 (-.0016, -.00047) $p < .001$	-.00086 (-.0014, -.00027) $p = .003$
Motor			-.00021 (-.00046, .000031) $p = .086$	-.0012 (-.0016, -.00085) $p < .001$	-.0011 (-.0015, -.00076) $p < .001$
Retail			-.00088 (-.0011, -.00063) $p < .001$	-.0017 (-.0021, -.0013) $p < .001$	-.0015 (-.0019, -.0011) $p < .001$
Services			-.00031 (-.00072, .000094) $p = .131$	-.0012 (-.0017, -.00074) $p < .001$	-.0010 (-.0016, -.00057) $p < .001$
Travel			-.00063 (-.0010, -.00027) $p < .001$	-.0013 (-.0017, -.00088) $p < .001$	-.0013 (-.0017, -.00088) $p < .001$
Other			.0019 (.0015, .0024) $p < .001$	-.0015 (-.0041, .0011) $p = .265$	-.0016 (-.0043, .0010) $p = .236$
<i>How individuals spend</i>					
ATM				.0035 (.00081, .0062) $p = .010$	.0038 (.0011, .0065) $p = .005$
Direct debit				.00099 (.00062, .0013) $p < .001$	.00092 (.00054, .0013) $p < .001$
Debit card				.0010 (.00076, .0014) $p < .001$	.0010 (.00067, .0013) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00070 (-.0010, -.00039) $p < .001$
Age					-.000097 (-.00010, -.000086) $p < .001$
Annual income (£'000s)					.0000022 (-.00000015, .0000045) $p = .067$
(Intercept)	.0035 (.0034, .0037) $p < .001$	.0035 (.0033, .0037) $p < .001$	.0028 (.0025, .0031) $p < .001$	.0027 (.0024, .0030) $p < .001$	.0067 (.0062, .0072) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.002
Observations	575 581	575 581	575 581	575 581	570 223

Supplementary Table S22

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00048 (.00036, .00059) $p < .001$	.00047 (.00036, .00059) $p < .001$	.00034 (.00022, .00046) $p < .001$	.00036 (.00024, .00048) $p < .001$	.00047 (.00034, .00059) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.000011 (-.000051, .000029) $p = .587$			
Communication			.0075 (.0062, .0088) $p < .001$	.0070 (.0057, .0084) $p < .001$	.0071 (.0057, .0084) $p < .001$
Financial services			-.000026 (-.000083, .000030) $p = .360$	-.00048 (-.00073, -.00022) $p < .001$	-.00044 (-.00070, -.00018) $p < .001$
Hobbies			.00029 (.00017, .00042) $p < .001$	-.00017 (-.00044, .000095) $p = .204$	-.00014 (-.00041, .00012) $p = .303$
Household bills			-.0024 (-.0030, -.0019) $p < .001$	-.0028 (-.0034, -.0022) $p < .001$	-.0018 (-.0024, -.0011) $p < .001$
Miscellaneous			.000094 (-.00025, .00044) $p = .595$	-.00038 (-.00080, .000047) $p = .081$	-.00033 (-.00076, .000089) $p = .121$
Motor			-.00015 (-.00033, .000034) $p = .109$	-.00061 (-.00092, -.00031) $p < .001$	-.00057 (-.00087, -.00027) $p < .001$
Retail			-.00057 (-.00075, -.00039) $p < .001$	-.00095 (-.0012, -.00068) $p < .001$	-.00082 (-.0011, -.00055) $p < .001$
Services			-.000030 (-.00033, .00027) $p = .843$	-.00044 (-.00082, -.000069) $p = .020$	-.00037 (-.00075, -.0000069) $p = .049$
Travel			-.00050 (-.00080, -.00020) $p < .001$	-.00077 (-.0011, -.00044) $p < .001$	-.00079 (-.0011, -.00046) $p < .001$
Other			.0016 (.0013, .0019) $p < .001$	-.00075 (-.0030, .0015) $p = .516$	-.00089 (-.0031, .0013) $p = .440$
<i>How individuals spend</i>					
ATM				.0024 (.00015, .0047) $p = .036$	.0027 (.00046, .0050) $p = .018$
Direct debit				.00039 (.00012, .00067) $p = .005$	.00036 (.000090, .00064) $p = .009$
Debit card				.00049 (.00024, .00073) $p < .001$	.00044 (.00020, .00069) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00030 (-.00052, -.000071) $p = .010$
Age					-.000053 (-.000061, -.000046) $p < .001$
Annual income (£'000s)					.00000027 (-.0000014, .0000019) $p = .749$
(Intercept)	.0019 (.0018, .0020) $p < .001$	.0019 (.0018, .0021) $p < .001$	.0017 (.0015, .0018) $p < .001$	.0016 (.0014, .0018) $p < .001$	.0038 (.0035, .0042) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.001
Observations	597 942	597 942	597 942	597 942	597 942

Supplementary Table S23

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00032 (.00020, .00043) $p < .001$	.00032 (.00020, .00043) $p < .001$	.00021 (.000094, .00033) $p < .001$	.00023 (.00011, .00035) $p < .001$	.00031 (.00019, .00043) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		.000000032 (-.000040, .000040) $p = .998$			
Communication			.0062 (.0049, .0075) $p < .001$	.0057 (.0044, .0071) $p < .001$	.0057 (.0044, .0071) $p < .001$
Financial services			-.000033 (-.000090, .000023) $p = .251$	-.00052 (-.00078, -.00027) $p < .001$	-.00050 (-.00076, -.00024) $p < .001$
Hobbies			.00027 (.00015, .00040) $p < .001$	-.00024 (-.00051, .000029) $p = .080$	-.00022 (-.00049, .000049) $p = .109$
Household bills			-.0017 (-.0023, -.0012) $p < .001$	-.0021 (-.0027, -.0015) $p < .001$	-.0013 (-.0020, -.00075) $p < .001$
Miscellaneous			.00032 (-.000024, .00067) $p = .068$	-.00019 (-.00062, .00023) $p = .375$	-.00016 (-.00059, .00026) $p = .440$
Motor			-.000074 (-.00026, .00011) $p = .433$	-.00058 (-.00088, -.00028) $p < .001$	-.00055 (-.00086, -.00025) $p < .001$
Retail			-.00045 (-.00064, -.00027) $p < .001$	-.00087 (-.0011, -.00060) $p < .001$	-.00078 (-.0010, -.00051) $p < .001$
Services			-.000083 (-.00038, .00022) $p = .590$	-.00053 (-.00091, -.00016) $p = .005$	-.00049 (-.00087, -.00011) $p = .010$
Travel			-.00023 (-.00053, .000062) $p = .121$	-.00052 (-.00086, -.00019) $p = .001$	-.00055 (-.00089, -.00022) $p = .001$
Other			.0011 (.00081, .0014) $p < .001$	-.0012 (-.0035, .00099) $p = .269$	-.0014 (-.0037, .00086) $p = .223$
<i>How individuals spend</i>					
ATM				.0024 (.00010, .0047) $p = .040$	.0026 (.00036, .0049) $p = .023$
Direct debit				.00043 (.00015, .00071) $p = .002$	.00041 (.00013, .00068) $p = .004$
Debit card				.00053 (.00028, .00078) $p < .001$	.00050 (.00026, .00075) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00022 (-.00044, .000086) $p = .059$
Age					-.000041 (-.000048, -.000033) $p < .001$
Annual income (£'000s)					-.00000021 (-.0000018, .0000014) $p = .803$
(Intercept)	.0019 (.0018, .0020) $p < .001$	.0019 (.0018, .0021) $p < .001$	.0017 (.0015, .0019) $p < .001$	.0017 (.0015, .0018) $p < .001$	.0033 (.0030, .0037) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.000	.000	.001
Observations	597 940	597 940	597 940	597 940	597 940

Supplementary Table S24

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0013 (.00070, .0020) $p < .001$	.0013 (.00062, .0020) $p < .001$	.0011 (.00039, .0018) $p = .002$	.0012 (.00046, .0019) $p = .001$	.0014 (.00060, .0021) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.00039 (-.00067, -.00010) $p = .007$			
Communication			.012 (.0044, .020) $p = .002$	.012 (.0046, .021) $p = .002$	.012 (.0045, .021) $p = .002$
Financial services			-.00034 (-.00087, .00018) $p = .205$	-.0015 (-.0030, -.000049) $p = .042$	-.0012 (-.0028, .00029) $p = .110$
Hobbies			.00021 (-.00074, .0011) $p = .663$	-.0015 (-.0032, .000033) $p = .054$	-.0015 (-.0032, .00010) $p = .066$
Household bills			-.0080 (-.011, -.0049) $p < .001$	-.0071 (-.010, -.0034) $p < .001$	-.0073 (-.011, -.0034) $p < .001$
Miscellaneous			-.00054 (-.0024, .0013) $p = .581$	-.0021 (-.0045, .00020) $p = .073$	-.0020 (-.0044, .00034) $p = .092$
Motor			-.00079 (-.0020, .00046) $p = .217$	-.0024 (-.0042, -.00065) $p = .007$	-.0023 (-.0041, -.00055) $p = .010$
Retail			-.00086 (-.0019, .00019) $p = .109$	-.0021 (-.0037, -.00061) $p = .006$	-.0023 (-.0039, -.00065) $p = .006$
Services			-.00058 (-.0027, .0016) $p = .602$	-.0020 (-.0045, .00048) $p = .113$	-.0024 (-.0050, .00018) $p = .068$
Travel			-.00031 (-.0020, .0014) $p = .728$	-.0010 (-.0029, .00085) $p = .282$	-.0010 (-.0030, .00084) $p = .271$
Other			.0022 (.00043, .0041) $p = .015$	-.0044 (-.018, .010) $p = .550$	-.0036 (-.018, .010) $p = .621$
<i>How individuals spend</i>					
ATM				.0066 (-.0079, .021) $p = .375$	.0060 (-.0086, .020) $p = .423$
Direct debit				.00013 (-.0016, .0018) $p = .880$	-.00031 (-.0021, .0015) $p = .734$
Debit card				.0019 (.00054, .0032) $p = .006$	.0018 (.00044, .0032) $p = .010$
<i>Demographics</i>					
Gender (0 = Male)					.000090 (-.0013, .0014) $p = .899$
Age					-.00017 (-.00023, -.00012) $p < .001$
Annual income (£'000s)					-.0000078 (-.000012, -.0000028) $p = .002$
(Intercept)	.0043 (.0036, .0049) $p < .001$	.0053 (.0043, .0064) $p < .001$	.0050 (.0037, .0062) $p < .001$	.0052 (.0039, .0064) $p < .001$	.012 (.010, .015) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.001	.002	.002	.004
Observations	37 470	37 470	37 470	37 470	36 902

Supplementary Table S25

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0018 (.00088, .0027) $p < .001$	.0016 (.00076, .0026) $p < .001$	.0014 (.00043, .0024) $p = .005$	.0015 (.00054, .0025) $p = .002$	.0010 (.00085, .0029) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.00063 (-.0010, -.00025) $p < .001$			
Communication			.013 (.0032, .024) $p = .010$	.014 (.0036, .025) $p = .009$	.014 (.0037, .026) $p = .008$
Financial services			-.00062 (-.0013, .000068) $p = .077$	-.0024 (-.0044, -.00048) $p = .015$	-.0020 (-.0041, .000033) $p = .053$
Hobbies			.00019 (-.0010, .0014) $p = .760$	-.0025 (-.0047, -.00032) $p = .024$	-.0023 (-.0045, -.000087) $p = .041$
Household bills			-.010 (-.014, -.0063) $p < .001$	-.0092 (-.014, -.0043) $p < .001$	-.0097 (-.015, -.0044) $p < .001$
Miscellaneous			-.00059 (-.0030, .0018) $p = .640$	-.0030 (-.0061, .000032) $p = .052$	-.0028 (-.0059, .00029) $p = .075$
Motor			-.00095 (-.0025, .00067) $p = .250$	-.0034 (-.0057, -.0010) $p = .004$	-.0031 (-.0055, -.00077) $p = .009$
Retail			-.0013 (-.0028, .00019) $p = .087$	-.0032 (-.0054, -.0010) $p = .003$	-.0033 (-.0056, -.0010) $p = .003$
Services			-.00066 (-.0036, .0022) $p = .657$	-.0029 (-.0063, .00046) $p = .089$	-.0033 (-.0068, .00011) $p = .058$
Travel			-.00024 (-.0026, .0021) $p = .841$	-.0012 (-.0037, .0013) $p = .341$	-.0012 (-.0038, .0013) $p = .337$
Other			.0029 (.00045, .0054) $p = .020$	-.0064 (-.024, .012) $p = .495$	-.0049 (-.023, .013) $p = .597$
<i>How individuals spend</i>					
ATM				.0092 (-.0093, .027) $p = .330$	.0082 (-.010, .026) $p = .384$
Direct debit				.00027 (-.0020, .0026) $p = .820$	-.00019 (-.0026, .0022) $p = .877$
Debit card				.0028 (.00099, .0047) $p = .002$	.0027 (.00078, .0046) $p = .005$
<i>Demographics</i>					
Gender (0 = Male)					.0020 (.00011, .0038) $p = .037$
Age					-.00026 (-.00033, -.00019) $p < .001$
Annual income (£'000s)					-.000010 (-.000017, -.0000039) $p = .002$
(Intercept)	.0068 (.0059, .0077) $p < .001$	.0086 (.0072, .0099) $p < .001$	.0082 (.0065, .0099) $p < .001$	.0085 (.0068, .010) $p < .001$	.018 (.015, .022) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.001	.002	.003	.005
Observations	32 453	32 453	32 453	32 453	31 957

Supplementary Table S26

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ (0 = didn't miss payments; 1 = missed payments) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0012 (.00060, .0018) $p < .001$	.0011 (.00055, .0018) $p < .001$	.0011 (.00044, .0018) $p = .001$	.0011 (.00050, .0018) $p < .001$	.0013 (.00060, .0020) $p < .001$
Control variables					
<i>What individuals spend</i>					
Month spend		-.00022 (-.00048, .000033) $p = .087$			
Communication			.011 (.0039, .018) $p = .002$	.012 (.0051, .020) $p < .001$	.012 (.0053, .020) $p < .001$
Financial services			-.00067 (-.0011, -.00018) $p = .006$	-.0010 (-.0023, .00032) $p = .137$	-.00087 (-.0022, .00047) $p = .204$
Hobbies			.00049 (-.00037, .0013) $p = .264$	-.00049 (-.0019, .00099) $p = .516$	-.00040 (-.0018, .0010) $p = .592$
Household bills			-.0045 (-.0074, -.0016) $p = .001$	-.0028 (-.0062, .00058) $p = .104$	-.0029 (-.0064, .00059) $p = .103$
Miscellaneous			.00052 (-.0011, .0022) $p = .547$	-.00027 (-.0023, .0018) $p = .795$	-.00018 (-.0022, .0019) $p = .863$
Motor			-.00068 (-.0018, .00048) $p = .249$	-.0014 (-.0031, .00014) $p = .075$	-.0013 (-.0029, .00026) $p = .101$
Retail			-.00042 (-.0013, .00046) $p = .349$	-.0010 (-.0023, .00037) $p = .154$	-.0010 (-.0024, .00031) $p = .128$
Services			.00074 (-.0012, .0027) $p = .464$	.00010 (-.0021, .0023) $p = .928$	-.000073 (-.0023, .0022) $p = .950$
Travel			.00041 (-.0013, .0021) $p = .644$	.00018 (-.0016, .0020) $p = .846$	.00024 (-.0016, .0020) $p = .793$
Other			.0014 (-.00016, .0031) $p = .078$	-.0040 (-.018, .010) $p = .594$	-.0035 (-.018, .011) $p = .642$
<i>How individuals spend</i>					
ATM				.0054 (-.0094, .020) $p = .470$	.0052 (-.0095, .020) $p = .485$
Direct debit				-.00078 (-.0023, .00080) $p = .333$	-.0010 (-.0026, .00058) $p = .211$
Debit card				.0010 (-.00020, .0022) $p = .102$	.00094 (-.00029, .0021) $p = .133$
<i>Demographics</i>					
Gender (0 = Male)					.00096 (-.00032, .0022) $p = .141$
Age					-.000087 (-.00013, -.000039) $p < .001$
Annual income (£'000s)					-.0000049 (-.0000095, -.0000028) $p = .037$
(Intercept)	.0032 (.0026, .0039) $p < .001$	.0039 (.0029, .0048) $p < .001$	.0034 (.0022, .0045) $p < .001$	.0036 (.0025, .0048) $p < .001$	.0070 (.0046, .0095) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.001	.001	.002	.003
Observations	33 702	33 702	33 702	33 702	33 702

Supplementary Table S27

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.00098 (.00035, .0016) $p = .002$	.00098 (.00036, .0016) $p = .001$	.00088 (.00020, .0015) $p = .010$	.00091 (.00023, .0015) $p = .008$	.00093 (.00025, .0016) $p = .007$
Control variables					
<i>What individuals spend</i>					
Month spend		.000029 (-.00023, .00029) $p = .822$			
Communication			.011 (.0044, .018) $p = .001$	.013 (.0061, .021) $p < .001$	.013 (.0061, .021) $p < .001$
Financial services			-.00035 (-.00084, .00013) $p = .151$	.00013 (-.0012, .0014) $p = .846$	.00019 (-.0011, .0015) $p = .779$
Hobbies			.00062 (-.00023, .0014) $p = .153$	.00068 (-.00079, .0021) $p = .364$	.00071 (-.00077, .0022) $p = .345$
Household bills			-.0011 (-.0040, .0017) $p = .435$	.00073 (-.0026, .0041) $p = .672$	.00078 (-.0027, .0043) $p = .661$
Miscellaneous			-.00067 (-.0023, .0010) $p = .439$	-.00049 (-.0025, .0016) $p = .646$	-.00045 (-.0025, .0016) $p = .669$
Motor			.00032 (-.00084, .0015) $p = .580$	.00047 (-.0011, .0021) $p = .570$	.00050 (-.0011, .0021) $p = .542$
Retail			-.00052 (-.0014, .00037) $p = .255$	-.00030 (-.0016, .0010) $p = .669$	-.00027 (-.0016, .0011) $p = .696$
Services			.0012 (-.00071, .0032) $p = .207$	.0015 (-.00076, .0038) $p = .192$	.0015 (-.00080, .0038) $p = .199$
Travel			-.0010 (-.0027, .00071) $p = .245$	-.00087 (-.0027, .00097) $p = .354$	-.00084 (-.0026, .00099) $p = .368$
Other			.0019 (.00026, .0035) $p = .022$	.0057 (-.0090, .020) $p = .444$	.0058 (-.0089, .020) $p = .437$
<i>How individuals spend</i>					
ATM				-.0038 (-.018, .011) $p = .607$	-.0039 (-.018, .010) $p = .603$
Direct debit				-.0013 (-.0029, .00028) $p = .107$	-.0013 (-.0030, .00021) $p = .090$
Debit card				-.000042 (-.0012, .0011) $p = .946$	-.000078 (-.0013, .0011) $p = .901$
<i>Demographics</i>					
Gender (0 = Male)					-.00000063 (-.0012, .0012) $p = .999$
Age					-.000026 (-.000075, .000021) $p = .283$
Annual income (£'000s)					-.00000096 (-.0000056, .0000036) $p = .682$
(Intercept)	.0032 (.0026, .0039) $p < .001$	.0032 (.0022, .0041) $p < .001$	.0024 (.0013, .0035) $p < .001$	.0026 (.0015, .0038) $p < .001$	.0038 (.0014, .0062) $p = .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.001
Observations	33 700	33 700	33 700	33 700	33 700

Supplementary Table S28

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

	(1)	(2)	(3)	(4)	(5)
Independent variable					
Entropy (1 month)	.0010 (.00037, .0017) $p = .002$	.0010 (.00037, .0017) $p = .002$	.00094 (.00021, .0016) $p = .011$	.0010 (.00029, .0017) $p = .005$	.0010 (.00030, .0018) $p = .006$
Control variables					
<i>What individuals spend</i>					
Month spend		.000036 (-.00018, .00025) $p = .741$			
Communication			.012 (.0040, .020) $p = .003$	.010 (.0017, .018) $p = .017$	.0095 (.00086, .018) $p = .031$
Financial services			-.000046 (-.00033, .00024) $p = .752$	-.0019 (-.0031, -.00062) $p = .003$	-.0019 (-.0032, -.00068) $p = .002$
Hobbies			.00089 (-.00042, .0022) $p = .184$	-.0011 (-.0029, .00061) $p = .201$	-.0012 (-.0030, .00061) $p = .195$
Household bills			-.0074 (-.011, -.0037) $p < .001$	-.0089 (-.012, -.0049) $p < .001$	-.0087 (-.012, -.0047) $p < .001$
Miscellaneous			-.00059 (-.0028, .0016) $p = .600$	-.0025 (-.0050, .000018) $p = .051$	-.0026 (-.0052, -.00012) $p = .039$
Motor			.00026 (-.00074, .0012) $p = .608$	-.0016 (-.0031, -.00014) $p = .031$	-.0017 (-.0032, -.00021) $p = .024$
Retail			-.00035 (-.0013, .00061) $p = .470$	-.0019 (-.0033, -.00062) $p = .004$	-.0021 (-.0035, -.00073) $p = .002$
Services			.00047 (-.0011, .0021) $p = .575$	-.0011 (-.0031, .00079) $p = .244$	-.0012 (-.0032, .00072) $p = .212$
Travel			.00013 (-.0014, .0016) $p = .868$	-.00078 (-.0024, .00087) $p = .352$	-.00087 (-.0025, .00080) $p = .309$
Other			.0030 (.0011, .0050) $p = .002$	-.0038 (-.014, .0066) $p = .475$	-.0040 (-.014, .0064) $p = .452$
<i>How individuals spend</i>					
ATM				.0069 (-.0037, .017) $p = .202$	.0072 (-.0033, .017) $p = .180$
Direct debit				.0017 (.00041, .0031) $p = .010$	.0017 (.00043, .0031) $p = .009$
Debit card				.0020 (.00087, .0032) $p < .001$	.0021 (.00093, .0033) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.000024 (-.0014, .0013) $p = .972$
Age					-.000050 (-.00011, .0000096) $p = .099$
Annual income (£'000s)					-.0000070 (-.000022, .0000079) $p = .354$
(Intercept)	.0050 (.0043, .0056) $p < .001$	.0049 (.0039, .0058) $p < .001$	.0046 (.0033, .0059) $p < .001$	.0045 (.0032, .0058) $p < .001$	.0066 (.0036, .0096) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.001
Observations	43 151	43 151	43 151	43 151	42 701

Supplementary Table S29

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0012 (.00042, .0021) $p = .003$	.0012 (.00040, .0021) $p = .003$	.0012 (.00031, .0021) $p = .008$	.0013 (.00045, .0022) $p = .003$	.0013 (.00043, .0023) $p = .006$
Control variables					
<i>What individuals spend</i>					
Month spend		-.00011 (-.00038, .00014) $p = .368$			
Communication			.013 (.0033, .024) $p = .009$	.010 (-.00051, .020) $p = .062$	.0087 (-.0021, .019) $p = .117$
Financial services			-.00022 (-.00056, .00011) $p = .197$	-.0031 (-.0046, -.0015) $p < .001$	-.0032 (-.0048, -.0016) $p < .001$
Hobbies			-.00023 (-.0018, .0013) $p = .771$	-.0029 (-.0051, -.00077) $p = .007$	-.0032 (-.0054, -.00097) $p = .004$
Household bills			-.010 (-.015, -.0063) $p < .001$	-.013 (-.018, -.0087) $p < .001$	-.013 (-.018, -.0088) $p < .001$
Miscellaneous			.0027 (.000041, .0054) $p = .046$	.00011 (-.0029, .0031) $p = .943$	-.00021 (-.0033, .0028) $p = .891$
Motor			-.00069 (-.0019, .00051) $p = .259$	-.0032 (-.0050, -.0014) $p < .001$	-.0034 (-.0052, -.0015) $p < .001$
Retail			-.000089 (-.0012, .0011) $p = .883$	-.0022 (-.0039, -.00058) $p = .008$	-.0025 (-.0043, -.00083) $p = .003$
Services			.0010 (-.00098, .0031) $p = .306$	-.0013 (-.0037, .0010) $p = .271$	-.0016 (-.0040, .00085) $p = .201$
Travel			-.00035 (-.0022, .0015) $p = .715$	-.0016 (-.0036, .00042) $p = .120$	-.0018 (-.0038, .00022) $p = .081$
Other			.0042 (.0018, .0066) $p < .001$	-.0049 (-.017, .0071) $p = .425$	-.0054 (-.017, .0067) $p = .384$
<i>How individuals spend</i>					
ATM				.0092 (-.0031, .021) $p = .142$	.0096 (-.0027, .022) $p = .127$
Direct debit				.0030 (.0013, .0046) $p < .001$	.0030 (.0014, .0047) $p < .001$
Debit card				.0027 (.0012, .0042) $p < .001$	.0028 (.0013, .0043) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00096 (-.0026, .00075) $p = .270$
Age					-.000068 (-.00014, .000068) $p = .074$
Annual income (£'000s)					-.000013 (-.000032, .000049) $p = .151$
(Intercept)	.0066 (.0057, .0074) $p < .001$	.0069 (.0058, .0080) $p < .001$	.0066 (.0050, .0082) $p < .001$	.0063 (.0047, .0079) $p < .001$	.0097 (.0059, .013) $p < .001$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.002	.002
Observations	37 222	37 222	37 222	37 222	36 833

Supplementary Table S30

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0015 (.00090, .0022) $p < .001$	.0015 (.00090, .0022) $p < .001$	.0017 (.00099, .0024) $p < .001$	.0017 (.0010, .0024) $p < .001$	.0016 (.00083, .0023) $p = .004$
Control variables					
<i>What individuals spend</i>					
Month spend		.000021 (-.00019, .00023) $p = .846$			
Communication			.019 (.011, .027) $p < .001$	.018 (.010, .026) $p < .001$	.016 (.0084, .025) $p < .001$
Financial services			-.00032 (-.00061, -.000037) $p = .027$	-.0017 (-.0030, -.00038) $p = .011$	-.0019 (-.0032, -.00059) $p = .004$
Hobbies			.0020 (.00097, .0031) $p < .001$	.000098 (-.0015, .0017) $p = .905$	-.00010 (-.0017, .0015) $p = .898$
Household bills			-.011 (-.015, -.0078) $p < .001$	-.012 (-.016, -.0084) $p < .001$	-.013 (-.017, -.0098) $p < .001$
Miscellaneous			.00021 (-.0016, .0020) $p = .814$	-.0013 (-.0035, .00090) $p = .242$	-.0016 (-.0038, .00064) $p = .162$
Motor			-.000062 (-.0011, .00098) $p = .906$	-.0018 (-.0034, -.00034) $p = .016$	-.0021 (-.0036, -.00057) $p = .007$
Retail			.00023 (-.00074, .0012) $p = .642$	-.0013 (-.0027, .000069) $p = .062$	-.0018 (-.0032, -.00033) $p = .015$
Services			.0013 (-.00029, .0029) $p = .108$	-.00015 (-.0021, .0017) $p = .872$	-.00050 (-.0024, .0014) $p = .610$
Travel			-.0013 (-.0029, .00035) $p = .121$	-.0020 (-.0037, -.00029) $p = .021$	-.0022 (-.0040, -.00052) $p = .010$
Other			.0057 (.0038, .0076) $p < .001$	-.0019 (-.015, .011) $p = .778$	-.0024 (-.015, .011) $p = .724$
<i>How individuals spend</i>					
ATM				.0075 (-.0059, .021) $p = .271$	.0075 (-.0059, .021) $p = .274$
Direct debit				.0011 (-.00024, .0025) $p = .106$	.0012 (-.00014, .0026) $p = .078$
Debit card				.0019 (.00072, .0032) $p = .001$	.0021 (.00088, .0033) $p < .001$
<i>Demographics</i>					
Gender (0 = Male)					-.00062 (-.0020, .00075) $p = .374$
Age					.000064 (.0000047, .00012) $p = .034$
Annual income (£'000s)					-.000017 (-.000032, -.0000034) $p = .015$
(Intercept)	.0046 (.0039, .0052) $p < .001$	.0045 (.0036, .0054) $p < .001$	.0034 (.0021, .0047) $p < .001$	.0033 (.0020, .0046) $p < .001$	.00091 (-.0020, .0039) $p = .552$
Individual fixed-effects	No	No	No	No	No
R^2	.001	.001	.003	.004	.004
Observations	39 166	39 166	39 166	39 166	39 166

Supplementary Table S31

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), spend by channel usage (£'000s) (4), and demographics (5).

Independent variable	(1)	(2)	(3)	(4)	(5)
Entropy (1 month)	.0010 (.00037, .0017) $p = .002$	.0010 (.00039, .0017) $p = .001$	.0011 (.00039, .0018) $p = .002$	.0011 (.00038, .0018) $p = .002$	.0010 (.00029, .0018) $p = .007$
Control variables					
<i>What individuals spend</i>					
Month spend		.00014 (-.000071, .00036) $p = .190$			
Communication			.011 (.0034, .019) $p = .005$	.011 (.0033, .019) $p = .005$	.010 (.0023, .018) $p = .012$
Financial services			-.00014 (-.00043, .00014) $p = .315$	-.00024 (-.0015, .0010) $p = .721$	-.00030 (-.0016, .0010) $p = .660$
Hobbies			.0014 (.00038, .0025) $p = .007$	.00092 (-.00071, .0025) $p = .268$	.00081 (-.00083, .0024) $p = .334$
Household bills			-.0041 (-.0079, -.00042) $p = .029$	-.0039 (-.0079, .000014) $p = .050$	-.0043 (-.0084, -.00033) $p = .033$
Miscellaneous			-.00022 (-.0020, .0016) $p = .809$	-.00044 (-.0026, .0018) $p = .700$	-.00051 (-.0027, .0017) $p = .651$
Motor			.000088 (-.00096, .0011) $p = .868$	-.00042 (-.0019, .0011) $p = .597$	-.00053 (-.0021, .0010) $p = .503$
Retail			.00013 (-.00084, .0011) $p = .792$	-.00027 (-.0017, .0011) $p = .704$	-.00036 (-.0018, .0011) $p = .630$
Services			.0015 (-.000073, .0031) $p = .061$	.0012 (-.00071, .0031) $p = .213$	.0011 (-.00080, .0031) $p = .247$
Travel			-.00024 (-.0019, .0014) $p = .775$	-.00040 (-.0021, .0013) $p = .652$	-.00048 (-.0022, .0012) $p = .589$
Other			.0034 (.0015, .0054) $p < .001$	-.0014 (-.014, .011) $p = .829$	-.0017 (-.015, .011) $p = .799$
<i>How individuals spend</i>					
ATM				.0049 (-.0085, .018) $p = .472$	.0049 (-.0086, .018) $p = .478$
Direct debit				-.00011 (-.0015, .0012) $p = .876$	-.000095 (-.0014, .0013) $p = .893$
Debit card				.00053 (-.00071, .0017) $p = .400$	.00058 (-.00067, .0018) $p = .363$
<i>Demographics</i>					
Gender (0 = Male)					-.0016 (-.0029, -.00020) $p = .024$
Age					.0000063 (-.000054, .000066) $p = .835$
Annual income (£'000s)					-.0000030 (-.000017, .000011) $p = .683$
(Intercept)	.0046 (.0039, .0052) $p < .001$	.0041 (.0032, .0051) $p < .001$	.0031 (.0018, .0044) $p < .001$	.0031 (.0018, .0044) $p < .001$	.0038 (.00083, .0068) $p = .012$
Individual fixed-effects	No	No	No	No	No
R^2	.000	.000	.001	.001	.002
Observations	39 164	39 164	39 164	39 164	39 164

Supplementary Table S32

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00070 (-.00048, .0018) $p = .244$	.00069 (-.00048, .0018) $p = .249$	.00068 (-.00056, .0019) $p = .282$	.00071 (-.00055, .0020) $p = .268$
Control variables				
<i>What individuals spend</i>				
Month spend		-.00015 (-.00033, .000032) $p = .106$		
Communication			-.00010 (-.012, .012) $p = .986$	-.00037 (-.012, .011) $p = .952$
Financial services			.000024 (-.00018, .00023) $p = .822$	-.00032 (-.0011, .00052) $p = .452$
Hobbies			-.00030 (-.00076, .00016) $p = .201$	-.00072 (-.0015, .00012) $p = .095$
Household bills			-.0026 (-.0085, .0031) $p = .370$	-.0028 (-.0087, .0030) $p = .343$
Miscellaneous			-.00043 (-.0053, .0044) $p = .863$	-.00081 (-.0057, .0040) $p = .745$
Motor			-.00057 (-.0011, .000025) $p = .060$	-.00098 (-.0018, .00014) $p = .021$
Retail			-.00045 (-.0015, .00066) $p = .427$	-.00066 (-.0017, .00040) $p = .222$
Services			-.00044 (-.0014, .00058) $p = .398$	-.00076 (-.0019, .00040) $p = .200$
Travel			-.00054 (-.0012, .00014) $p = .124$	-.00082 (-.0015, .000051) $p = .036$
Other			.0010 (-.0012, .0033) $p = .353$	.00029 (-.00094, .0015) $p = .640$
<i>How individuals spend</i>				
ATM				.00094 (-.0026, .0045) $p = .607$
Direct debit				.00026 (-.00059, .0011) $p = .547$
Debit card				.00045 (-.00030, .0012) $p = .241$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.292	.292	.292	.292
Observations	163 892	163 892	163 892	163 892

Supplementary Table S33

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	-.00058 (-.0022, .0010) $p = .495$	-.00057 (-.0022, .0010) $p = .499$	-.00066 (-.0024, .0010) $p = .457$	-.00062 (-.0024, .0011) $p = .486$
Control variables				
<i>What individuals spend</i>				
Month spend		.000073 (-.00015, .00030) $p = .534$		
Communication			.00096 (-.020, .022) $p = .931$	.00040 (-.021, .022) $p = .970$
Financial services			.000097 (-.00019, .00038) $p = .509$	-.00055 (-.0017, .00066) $p = .374$
Hobbies			.00032 (-.00025, .00089) $p = .271$	-.00049 (-.0016, .00070) $p = .419$
Household bills			.0023 (-.0047, .0095) $p = .515$	.0020 (-.0050, .0092) $p = .566$
Miscellaneous			-.0025 (-.0063, .0012) $p = .186$	-.0033 (-.0072, .00066) $p = .102$
Motor			-.000042 (-.0010, .00094) $p = .931$	-.00080 (-.0021, .00049) $p = .224$
Retail			-.00032 (-.0016, .00098) $p = .629$	-.00071 (-.0020, .00062) $p = .295$
Services			-.00028 (-.0018, .0012) $p = .725$	-.00086 (-.0025, .00084) $p = .321$
Travel			.00012 (-.00058, .00082) $p = .734$	-.00040 (-.0014, .00062) $p = .444$
Other			.00060 (-.0022, .0034) $p = .678$	-.00025 (-.0017, .0011) $p = .726$
<i>How individuals spend</i>				
ATM				.00087 (-.0033, .0050) $p = .680$
Direct debit				.00050 (-.00072, .0017) $p = .421$
Debit card				.00084 (-.00025, .0019) $p = .130$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.399	.399	.399	.399
Observations	141 190	141 190	141 190	141 190

Supplementary Table S34

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00013 (-.00043, .00071) $p = .636$	.00014 (-.00043, .00071) $p = .632$	.00017 (-.00047, .00082) $p = .589$	.00022 (-.00045, .00088) $p = .520$
Control variables				
<i>What individuals spend</i>				
Month spend		.000022 (-.000074, .00011) $p = .646$		
Communication			-.0099 (-.018, -.0019) $p = .014$	-.010 (-.018, -.0021) $p = .013$
Financial services			.000026 (-.000081, .00013) $p = .628$	-.00012 (-.00064, .00038) $p = .622$
Hobbies			.00000048 (-.00022, .00022) $p = .996$	-.00011 (-.00053, .00030) $p = .593$
Household bills			.00050 (-.0012, .0022) $p = .578$	.00042 (-.0013, .0022) $p = .637$
Miscellaneous			-.000058 (-.00074, .00063) $p = .868$	-.00019 (-.00099, .00060) $p = .633$
Motor			.000055 (-.000054, .00016) $p = .320$	-.000056 (-.00043, .00032) $p = .769$
Retail			.000036 (-.00055, .00063) $p = .903$	-.000016 (-.00050, .00047) $p = .946$
Services			-.000050 (-.00025, .00015) $p = .633$	-.00014 (-.00051, .00021) $p = .431$
Travel			.000017 (-.00027, .00031) $p = .909$	-.000023 (-.00031, .00026) $p = .875$
Other			.00057 (-.0015, .0026) $p = .586$	.00012 (-.0013, .0016) $p = .869$
<i>How individuals spend</i>				
ATM				.00045 (-.0021, .0030) $p = .730$
Direct debit				.00017 (-.00035, .00071) $p = .509$
Debit card				.00012 (-.00027, .00052) $p = .539$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.305	.305	.305	.305
Observations	149 493	149 493	149 493	149 493

Supplementary Table S35

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (no direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00021 (-.00032, .00075) $p = .441$	.00021 (-.00032, .00075) $p = .440$	.000088 (-.00049, .00067) $p = .767$	.000074 (-.00051, .00066) $p = .805$
Control variables				
<i>What individuals spend</i>				
Month spend		.0000063 (-.000097, .00011) $p = .904$		
Communication			.023 (.0019, .044) $p = .032$	.023 (.0020, .045) $p = .031$
Financial services			.000040 (-.000068, .00014) $p = .470$	.00023 (-.00032, .00078) $p = .412$
Hobbies			.000034 (-.00047, .00054) $p = .892$	.00019 (-.00065, .0010) $p = .651$
Household bills			.00068 (-.0011, .0025) $p = .464$	.00077 (-.0011, .0026) $p = .421$
Miscellaneous			.00015 (-.00071, .0010) $p = .721$	.00033 (-.00068, .0013) $p = .518$
Motor			-.000015 (-.00012, .000096) $p = .781$	-.00014 (-.00035, .00064) $p = .578$
Retail			-.00028 (-.00093, .00037) $p = .404$	-.00020 (-.00078, .00038) $p = .500$
Services			-.00025 (-.00054, .000032) $p = .081$	-.00012 (-.00057, .00032) $p = .587$
Travel			-.00044 (-.00091, .000013) $p = .057$	-.00039 (-.00083, .000049) $p = .081$
Other			-.00014 (-.0025, .0022) $p = .903$	.0016 (-.0013, .0046) $p = .282$
<i>How individuals spend</i>				
ATM				-.0018 (-.0056, .0019) $p = .338$
Direct debit				-.00020 (-.00073, .00033) $p = .460$
Debit card				-.00017 (-.00070, .00034) $p = .504$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.254	.254	.255	.255
Observations	149 489	149 489	149 489	149 489

Supplementary Table S36

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00060 (-.00064, .0018) $p = .341$	.00061 (-.00064, .0018) $p = .339$	.00076 (-.00055, .0020) $p = .254$	.00080 (-.00052, .0021) $p = .235$
Control variables				
<i>What individuals spend</i>				
Month spend		.000040 (-.000050, .00013) $p = .378$		
Communication			-.0028 (-.0093, .0037) $p = .397$	-.0031 (-.0096, .0034) $p = .350$
Financial services			.000026 (-.000043, .000095) $p = .465$	-.00038 (-.0012, .00043) $p = .357$
Hobbies			.00078 (-.00068, .0022) $p = .295$	.00045 (-.0010, .0019) $p = .561$
Household bills			.0014 (-.0021, .0049) $p = .431$	.0011 (-.0023, .0047) $p = .513$
Miscellaneous			-.00020 (-.0010, .00063) $p = .624$	-.00060 (-.0019, .00076) $p = .387$
Motor			-.00031 (-.00064, .000019) $p = .065$	-.00065 (-.0014, .00016) $p = .116$
Retail			.00037 (-.00047, .0012) $p = .388$	.00016 (-.00055, .00087) $p = .658$
Services			-.00074 (-.0013, -.00015) $p = .014$	-.0010 (-.0018, -.00022) $p = .011$
Travel			.00048 (-.00035, .0013) $p = .260$	.00037 (-.00055, .0013) $p = .431$
Other			.0021 (-.0023, .0065) $p = .349$	-.00092 (-.0040, .0022) $p = .565$
<i>How individuals spend</i>				
ATM				.0034 (-.0029, .0097) $p = .288$
Direct debit				.00050 (-.00034, .0013) $p = .248$
Debit card				.00037 (-.00045, .0012) $p = .372$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.281	.281	.281	.281
Observations	100 257	100 257	100 257	100 257

Supplementary Table S37

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	-.00075 (-.0025, .00099) $p = .397$	-.00075 (-.0025, .00099) $p = .398$	-.00073 (-.0025, .0011) $p = .432$	-.00074 (-.0026, .0011) $p = .430$
Control variables				
<i>What individuals spend</i>				
Month spend		.000010 (-.000088, .00010) $p = .829$		
Communication			.0010 (-.0045, .0066) $p = .718$	.0013 (-.0044, .0070) $p = .647$
Financial services			.0000034 (-.000066, .000073) $p = .923$	.00032 (-.00086, .0015) $p = .591$
Hobbies			-.00047 (-.0017, .00075) $p = .446$	-.00016 (-.0016, .0013) $p = .830$
Household bills			-.00079 (-.0046, .0030) $p = .687$	-.00034 (-.0043, .0036) $p = .864$
Miscellaneous			-.00040 (-.0017, .00095) $p = .562$	-.000058 (-.0017, .0016) $p = .945$
Motor			.00040 (-.00056, .0013) $p = .416$	.00073 (-.00061, .0020) $p = .286$
Retail			-.00016 (-.0015, .0012) $p = .813$	.000013 (-.0011, .0012) $p = .982$
Services			-.00022 (-.0015, .0010) $p = .740$	.0000083 (-.0015, .0016) $p = .991$
Travel			-.00025 (-.00098, .00048) $p = .503$	-.000096 (-.00090, .00070) $p = .813$
Other			.0035 (-.00080, .0078) $p = .111$	-.0033 (-.010, .0038) $p = .361$
<i>How individuals spend</i>				
ATM				.0076 (-.0015, .016) $p = .101$
Direct debit				-.00021 (-.0014, .00096) $p = .716$
Debit card				-.00036 (-.0015, .00082) $p = .548$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.439	.439	.439	.439
Observations	85 458	85 458	85 458	85 458

Supplementary Table S38

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	-.000013 (-.00042, .00040) $p = .950$	-.000012 (-.00042, .00040) $p = .952$	.000040 (-.00040, .00048) $p = .859$	.000040 (-.00040, .00048) $p = .858$
Control variables				
<i>What individuals spend</i>				
Month spend		.0000057 (-.000014, .000025) $p = .575$		
Communication			-.00023 (-.0016, .0011) $p = .742$	-.00019 (-.0016, .0012) $p = .791$
Financial services			.0000082 (-.0000055, .000022) $p = .243$	.000044 (-.00016, .00025) $p = .675$
Hobbies			-.00022 (-.00073, .00027) $p = .377$	-.00019 (-.00072, .00032) $p = .458$
Household bills			-.00043 (-.0010, .00015) $p = .149$	-.00039 (-.0010, .00022) $p = .215$
Miscellaneous			.000061 (-.000088, .00021) $p = .422$	.000095 (-.00019, .00039) $p = .526$
Motor			-.000060 (-.00015, .000037) $p = .225$	-.000028 (-.00019, .00014) $p = .741$
Retail			.00010 (-.00012, .00033) $p = .373$	.00012 (-.00017, .00041) $p = .410$
Services			-.000064 (-.00023, .00010) $p = .465$	-.000041 (-.00019, .00011) $p = .592$
Travel			-.000033 (-.00014, .000074) $p = .544$	-.000019 (-.00011, .000071) $p = .677$
Other			.00070 (-.00037, .0017) $p = .199$	.00018 (-.00012, .00049) $p = .248$
<i>How individuals spend</i>				
ATM				.00060 (-.00066, .0018) $p = .350$
Direct debit				-.000038 (-.00023, .00015) $p = .701$
Debit card				-.000034 (-.00024, .00017) $p = .744$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.229	.229	.229	.229
Observations	91 526	91 526	91 526	91 526

Supplementary Table S39

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for credit cards (direct debit), as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00033 (-.0000016, .00066) $p = .051$	.00033 (-.00000024, .00066) $p = .050$	.00030 (-.000073, .00067) $p = .115$	.00029 (-.000082, .00067) $p = .125$
Control variables				
<i>What individuals spend</i>				
Month spend		.000033 (-.0000029, .000096) $p = .297$		
Communication			.00040 (-.0015, .0023) $p = .690$	.00064 (-.0014, .0027) $p = .547$
Financial services			.000039 (-.000031, .00011) $p = .273$	.00025 (-.000098, .00061) $p = .156$
Hobbies			-.000085 (-.00044, .00027) $p = .640$	.000090 (-.00035, .00054) $p = .694$
Household bills			-.000029 (-.00048, .00042) $p = .901$	.00017 (-.00037, .00073) $p = .526$
Miscellaneous			.00035 (-.00058, .0012) $p = .459$	.00055 (-.00035, .0014) $p = .229$
Motor			-.00018 (-.00048, .00010) $p = .210$	-.0000015 (-.00039, .00038) $p = .993$
Retail			-.00012 (-.00063, .00037) $p = .615$	-.000024 (-.00053, .00048) $p = .926$
Services			-.00010 (-.00027, .000070) $p = .249$	.000037 (-.00021, .00028) $p = .765$
Travel			.00021 (-.00028, .00072) $p = .400$	.00028 (-.00021, .00077) $p = .261$
Other			.0014 (-.00032, .0033) $p = .108$	.00011 (-.00043, .00066) $p = .679$
<i>How individuals spend</i>				
ATM				.0016 (-.00030, .0036) $p = .097$
Direct debit				-.00025 (-.00062, .00011) $p = .182$
Debit card				-.00020 (-.00054, .00014) $p = .245$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.305	.305	.305	.305
Observations	91 526	91 526	91 526	91 526

Supplementary Table S40

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00025 (.000017, .00048) $p = .035$	.00024 (.000010, .00048) $p = .040$	.00012 (-.00011, .00037) $p = .307$	.00013 (-.00012, .00038) $p = .320$
Control variables				
<i>What individuals spend</i>				
Month spend		-.000065 (-.00010, -.000022) $p = .003$		
Communication			.000036 (-.0021, .0022) $p = .973$	.00019 (-.0019, .0023) $p = .857$
Financial services			-.000018 (-.000040, .0000041) $p = .111$	.00016 (-.000065, .00038) $p = .163$
Hobbies			-.000018 (-.00057, .00054) $p = .947$	.00016 (-.00042, .00076) $p = .578$
Household bills			-.0011 (-.0021, -.00010) $p = .030$	-.00095 (-.0019, .000070) $p = .068$
Miscellaneous			-.000025 (-.00026, .00020) $p = .832$	.00016 (-.00016, .00048) $p = .339$
Motor			-.00013 (-.00019, -.000068) $p < .001$	.000049 (-.00017, .00027) $p = .666$
Retail			-.00060 (-.00090, -.00029) $p < .001$	-.00044 (-.00074, -.00014) $p = .003$
Services			-.00019 (-.00043, .000037) $p = .099$	-.00033 (-.00031, .00024) $p = .814$
Travel			-.000065 (-.00025, .00012) $p = .492$	.000071 (-.00014, .00029) $p = .525$
Other			-.00036 (-.0010, .00035) $p = .324$	-.00051 (-.0018, .00086) $p = .468$
<i>How individuals spend</i>				
ATM				.00017 (-.0013, .0017) $p = .821$
Direct debit				-.00014 (-.00037, .000096) $p = .245$
Debit card				-.00018 (-.00041, .000036) $p = .100$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.416	.416	.416	.416
Observations	666 918	666 918	666 918	666 918

Supplementary Table S41

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00016 (-.00010, .00044) $p = .236$	.00016 (-.00011, .00043) $p = .247$	.000078 (-.00021, .00036) $p = .595$	.000079 (-.00021, .00037) $p = .591$
Control variables				
<i>What individuals spend</i>				
Month spend		-.000044 (-.000098, .000010) $p = .110$		
Communication			-.00078 (-.0040, .0025) $p = .639$	-.00080 (-.0040, .0024) $p = .632$
Financial services			-.000019 (-.000048, .0000088) $p = .177$	-.000040 (-.00029, .00021) $p = .759$
Hobbies			-.000085 (-.00098, .00081) $p = .852$	-.00010 (-.0010, .00079) $p = .816$
Household bills			-.00068 (-.0018, .00049) $p = .254$	-.00070 (-.0018, .00047) $p = .240$
Miscellaneous			-.00000084 (-.00024, .00024) $p = .994$	-.000022 (-.00034, .00030) $p = .890$
Motor			-.000030 (-.00016, .00010) $p = .648$	-.000053 (-.00032, .00021) $p = .697$
Retail			-.00043 (-.00073, -.00014) $p = .003$	-.00046 (-.00075, -.00016) $p = .002$
Services			-.000022 (-.00021, .00017) $p = .818$	-.000041 (-.00033, .00024) $p = .781$
Travel			-.000045 (-.00029, .00020) $p = .719$	-.000060 (-.00033, .00021) $p = .665$
Other			-.00011 (-.0010, .00081) $p = .809$	-.00010 (-.0027, .00068) $p = .234$
<i>How individuals spend</i>				
ATM				.0010 (-.0010, .0030) $p = .327$
Direct debit				.000010 (-.00026, .00028) $p = .938$
Debit card				.000023 (-.00023, .00027) $p = .858$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.516	.516	.516	.516
Observations	575 581	575 581	575 581	575 581

Supplementary Table S42

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.000092 (-.00013, .00032) $p = .432$	.000094 (-.00013, .00032) $p = .424$	.00011 (-.00012, .00035) $p = .361$	.00014 (-.00011, .00038) $p = .279$
Control variables				
<i>What individuals spend</i>				
Month spend		.000012 (-.000021, .000046) $p = .462$		
Communication			-.00082 (-.0036, .0019) $p = .562$	-.00074 (-.0035, .0020) $p = .599$
Financial services			.0000059 (-.0000093, .000021) $p = .446$	.000080 (-.00017, .00033) $p = .536$
Hobbies			.000091 (-.00028, .00046) $p = .634$	.00017 (-.00024, .00060) $p = .414$
Household bills			-.00035 (-.0012, .00053) $p = .431$	-.00028 (-.0011, .00061) $p = .533$
Miscellaneous			-.0000020 (-.00024, .00023) $p = .986$	.000080 (-.00025, .00041) $p = .636$
Motor			-.000035 (-.000091, .000019) $p = .207$	.000047 (-.00019, .00029) $p = .699$
Retail			-.0000044 (-.00022, .00021) $p = .969$	.000065 (-.00017, .00030) $p = .587$
Services			.000048 (-.00014, .00023) $p = .620$	.00012 (-.00019, .00043) $p = .449$
Travel			-.000098 (-.00027, .000076) $p = .270$	-.000037 (-.00022, .00014) $p = .688$
Other			.00068 (-.0000018, .0013) $p = .050$	-.00044 (-.0016, .00080) $p = .488$
<i>How individuals spend</i>				
ATM				.0011 (-.00023, .0026) $p = .101$
Direct debit				-.000048 (-.00031, .00021) $p = .713$
Debit card				-.000085 (-.00034, .00017) $p = .512$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.285	.285	.285	.285
Observations	597 942	597 942	597 942	597 942

Supplementary Table S43

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for PCAs, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00013 (-.00011, .00038) $p = .305$	.00013 (-.00011, .00038) $p = .300$	.00011 (-.00015, .00037) $p = .405$	.00011 (-.00014, .00038) $p = .393$
Control variables				
<i>What individuals spend</i>				
Month spend		.0000080 (-.000039, .000055) $p = .742$		
Communication			.00048 (-.0019, .0029) $p = .699$	.00034 (-.0021, .0028) $p = .783$
Financial services			-.0000073 (-.000028, .000013) $p = .500$	-.00015 (-.00042, .00011) $p = .259$
Hobbies			.000070 (-.00038, .00052) $p = .762$	-.000083 (-.00056, .00039) $p = .733$
Household bills			.00027 (-.00072, .0012) $p = .592$	.00013 (-.00084, .0011) $p = .790$
Miscellaneous			.00032 (-.00050, .0011) $p = .444$	.00017 (-.00070, .0010) $p = .702$
Motor			.000066 (-.000053, .00018) $p = .276$	-.000084 (-.00036, .00020) $p = .561$
Retail			-.000010 (-.00030, .00028) $p = .943$	-.00013 (-.00046, .00018) $p = .400$
Services			-.000032 (-.00031, .00025) $p = .825$	-.00017 (-.00053, .00018) $p = .350$
Travel			.000084 (-.00016, .00033) $p = .512$	-.000020 (-.00025, .00020) $p = .859$
Other			-.00048 (-.0011, .00021) $p = .175$	-.00091 (-.0021, .00034) $p = .156$
<i>How individuals spend</i>				
ATM				.00042 (-.0010, .0018) $p = .561$
Direct debit				.00013 (-.00014, .00040) $p = .355$
Debit card				.00015 (-.00011, .00043) $p = .265$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.246	.246	.246	.246
Observations	597 940	597 940	597 940	597 940

Supplementary Table S44

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00042 (-.00086, .0017) $p = .517$	.00039 (-.00087, .0016) $p = .539$	.00054 (-.00078, .0018) $p = .421$	.00055 (-.00077, .0019) $p = .417$
Control variables				
<i>What individuals spend</i>				
Month spend		-.00016 (-.00052, .00018) $p = .346$		
Communication			-.0065 (-.030, .017) $p = .594$	-.0068 (-.030, .017) $p = .578$
Financial services			-.00018 (-.00056, .00019) $p = .332$	-.00035 (-.0014, .00074) $p = .524$
Hobbies			-.00042 (-.0011, .00031) $p = .260$	-.00054 (-.0019, .00084) $p = .443$
Household bills			-.0025 (-.0061, .00098) $p = .156$	-.0027 (-.0063, .00096) $p = .147$
Miscellaneous			-.0000067 (-.00047, .00046) $p = .977$	-.00013 (-.0013, .0010) $p = .830$
Motor			-.00014 (-.00036, .000071) $p = .187$	-.00025 (-.0013, .00084) $p = .647$
Retail			.000085 (-.00090, .0010) $p = .865$	-.000031 (-.00096, .00090) $p = .948$
Services			-.00088 (-.0017, .000016) $p = .054$	-.0010 (-.0025, .00058) $p = .214$
Travel			-.00052 (-.0025, .0015) $p = .614$	-.00058 (-.0023, .0011) $p = .519$
Other			.00015 (-.0021, .0053) $p = .408$	-.00081 (-.0034, .0018) $p = .548$
<i>How individuals spend</i>				
ATM				.0025 (-.0023, .0073) $p = .313$
Direct debit				.00045 (-.00097, .0018) $p = .534$
Debit card				.00012 (-.0010, .0013) $p = .833$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.356	.356	.356	.356
Observations	37 470	37 470	37 470	37 470

Supplementary Table S45

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00048 (-.0012, .0022) $p = .585$	.00044 (-.0012, .0021) $p = .615$	.00076 (-.0010, .0025) $p = .407$	.00077 (-.0010, .0026) $p = .403$
Control variables				
<i>What individuals spend</i>				
Month spend		-.00030 (-.00072, .00011) $p = .157$		
Communication			-.024 (-.060, .010) $p = .170$	-.025 (-.060, .0099) $p = .160$
Financial services			-.00047 (-.0010, .000075) $p = .090$	-.0011 (-.0023, .000084) $p = .068$
Hobbies			-.00046 (-.0012, .00029) $p = .228$	-.0010 (-.0024, .00037) $p = .147$
Household bills			-.0051 (-.012, .0016) $p = .138$	-.0057 (-.012, .0010) $p = .098$
Miscellaneous			.00011 (-.00042, .00064) $p = .684$	-.00053 (-.0018, .00079) $p = .433$
Motor			-.000090 (-.00036, .00018) $p = .519$	-.00068 (-.0018, .00047) $p = .247$
Retail			.00085 (-.00046, .0021) $p = .205$	.00031 (-.0010, .0016) $p = .644$
Services			-.00096 (-.0021, .00024) $p = .117$	-.0015 (-.0031, .000061) $p = .059$
Travel			.00061 (-.0011, .0023) $p = .490$	.00025 (-.0012, .0017) $p = .750$
Other			-.0017 (-.0059, .0025) $p = .426$	-.0016 (-.0056, .0024) $p = .433$
<i>How individuals spend</i>				
ATM				-.00017 (-.0064, .0060) $p = .955$
Direct debit				.00089 (-.00093, .0027) $p = .339$
Debit card				.00064 (-.00064, .0019) $p = .326$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.449	.449	.450	.450
Observations	32 453	32 453	32 453	32 453

Supplementary Table S46

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	-0.00017 (-.0013, .0010) $p = .773$	-0.00019 (-.0014, .0010) $p = .757$	-0.00034 (-.0015, .00091) $p = .595$	-0.00028 (-.0016, .00099) $p = .667$
Control variables				
<i>What individuals spend</i>				
Month spend		-0.000071 (-.00045, .00031) $p = .716$		
Communication			-0.0012 (-.021, .018) $p = .899$	-0.0012 (-.021, .019) $p = .902$
Financial services			-0.00013 (-.00054, .00026) $p = .503$	-0.00029 (-.0015, .0010) $p = .656$
Hobbies			.00043 (-.00090, .0017) $p = .526$	.00025 (-.0014, .0019) $p = .767$
Household bills			.0011 (-.0031, .0053) $p = .604$	.00097 (-.0032, .0051) $p = .650$
Miscellaneous			.00090 (-.00024, .0020) $p = .124$	.00070 (-.0011, .0025) $p = .447$
Motor			-0.00037 (-.0010, .00029) $p = .271$	-0.00055 (-.0019, .00085) $p = .437$
Retail			-0.00020 (-.0014, .0010) $p = .750$	-0.00034 (-.0018, .0011) $p = .646$
Services			-0.00096 (-.0029, .0027) $p = .947$	-0.00026 (-.0034, .0028) $p = .868$
Travel			.0013 (-.0013, .0040) $p = .313$	.0012 (-.0019, .0044) $p = .444$
Other			-0.0031 (-.0065, .00027) $p = .071$	-0.0014 (-.0038, .00092) $p = .231$
<i>How individuals spend</i>				
ATM				-0.0017 (-.0053, .0018) $p = .342$
Direct debit				-0.00011 (-.0017, .0015) $p = .895$
Debit card				.00018 (-.0012, .0016) $p = .795$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.228	.228	.229	.229
Observations	33 702	33 702	33 702	33 702

Supplementary Table S47

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for loans, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.000025 (-.0012, .0012) $p = .968$	.000063 (-.0012, .0013) $p = .921$	-.00011 (-.0014, .0012) $p = .870$	-.00012 (-.0014, .0012) $p = .858$
Control variables				
<i>What individuals spend</i>				
Month spend		.00020 (-.00030, .00071) $p = .431$		
Communication			-.0012 (-.021, .019) $p = .906$	-.00018 (-.020, .020) $p = .986$
Financial services			.00013 (-.00031, .00058) $p = .555$	.0010 (-.00087, .0029) $p = .284$
Hobbies			.0012 (-.0015, .0040) $p = .373$	.0020 (-.0014, .0055) $p = .249$
Household bills			.00098 (-.0024, .0044) $p = .577$	.0018 (-.0017, .0054) $p = .319$
Miscellaneous			-.00087 (-.0023, .00065) $p = .261$	-.000027 (-.0025, .0024) $p = .982$
Motor			.00089 (-.0014, .0032) $p = .453$	.0016 (-.0010, .0043) $p = .219$
Retail			-.00071 (-.0017, .00033) $p = .183$	-.0000097 (-.0017, .0016) $p = .990$
Services			.00088 (-.0018, .0036) $p = .529$	.0016 (-.0023, .0056) $p = .420$
Travel			-.00083 (-.0024, .00079) $p = .315$	-.00036 (-.0024, .0017) $p = .737$
Other			.0011 (-.0040, .0063) $p = .661$	.0015 (-.010, .013) $p = .801$
<i>How individuals spend</i>				
ATM				-.00038 (-.013, .012) $p = .953$
Direct debit				-.0015 (-.0037, .00068) $p = .176$
Debit card				-.00085 (-.0028, .0011) $p = .393$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.175	.175	.175	.175
Observations	33 700	33 700	33 700	33 700

Supplementary Table S48

Predicting whether an individual in the LBG dataset missed a payment in month $t = 1$ (0 = didn't miss a payment; 1 = missed a payment) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

	(1)	(2)	(3)	(4)
Independent variable				
Entropy (1 month)	.00054 (-.00072, .0018) $p = .401$	.00055 (-.00072, .0018) $p = .396$	.00030 (-.00099, .0016) $p = .648$	.00031 (-.00099, .0016) $p = .640$
Control variables				
<i>What individuals spend</i>				
Month spend		.000094 (-.00013, .00032) $p = .416$		
Communication			-.00073 (-.013, .012) $p = .912$	-.0018 (-.015, .011) $p = .781$
Financial services			-.00099 (-.00012, .00032) $p = .380$	-.00075 (-.0021, .00061) $p = .280$
Hobbies			.0013 (-.00088, .0035) $p = .242$	.00028 (-.0022, .0028) $p = .827$
Household bills			-.00073 (-.0087, .0073) $p = .858$	-.0016 (-.0099, .0066) $p = .704$
Miscellaneous			-.0012 (-.0026, .00011) $p = .071$	-.0022 (-.0041, -.00032) $p = .021$
Motor			-.00032 (-.00066, .0013) $p = .518$	-.00064 (-.0021, .00082) $p = .388$
Retail			-.00068 (-.0019, .00061) $p = .301$	-.0015 (-.0029, -.00015) $p = .029$
Services			-.00074 (-.0021, .0019) $p = .943$	-.00091 (-.0033, .0014) $p = .455$
Travel			.00071 (-.0012, .0026) $p = .478$	.00012 (-.0015, .0018) $p = .883$
Other			-.0012 (-.0073, .0048) $p = .694$	-.0046 (-.011, .0018) $p = .162$
<i>How individuals spend</i>				
ATM				.0036 (-.0046, .011) $p = .391$
Direct debit				.00070 (-.00063, .0020) $p = .301$
Debit card				.0010 (-.00027, .0023) $p = .121$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.321	.321	.321	.321
Observations	43 151	43 151	43 151	43 151

Supplementary Table S49

Predicting whether an individual in the LBG dataset missed a payment in month $t = 3$ (0 = didn't miss a payment; 1 = missed a payment) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	-0.00061 (-.0022, .0010) $p = .465$	-0.00061 (-.0022, .0010) $p = .461$	-0.00065 (-.0022, .00098) $p = .432$	-0.00061 (-.0022, .0010) $p = .470$
Control variables				
<i>What individuals spend</i>				
Month spend		-.00011 (-.00031, .000091) $p = .280$		
Communication			-.0075 (-.024, .0091) $p = .376$	-.0086 (-.025, .0082) $p = .316$
Financial services			-.00011 (-.00024, .000019) $p = .094$	-.0013 (-.0028, .00012) $p = .073$
Hobbies			.000036 (-.00056, .00063) $p = .905$	-.00091 (-.0025, .00066) $p = .256$
Household bills			.0013 (-.0041, .0068) $p = .628$	.00044 (-.0052, .0061) $p = .878$
Miscellaneous			.0036 (-.0028, .010) $p = .267$	.0026 (-.0038, .0091) $p = .431$
Motor			-.00065 (-.0013, .000018) $p = .056$	-.0015 (-.0031, .000032) $p = .054$
Retail			.000052 (-.00095, .0010) $p = .919$	-.00069 (-.0022, .00081) $p = .366$
Services			.00023 (-.0028, .0032) $p = .880$	-.00067 (-.0036, .0022) $p = .657$
Travel			-.000093 (-.0018, .0016) $p = .916$	-.00062 (-.0024, .0012) $p = .507$
Other			-.0039 (-.011, .0031) $p = .272$	-.0050 (-.011, .0017) $p = .143$
<i>How individuals spend</i>				
ATM				.0010 (-.0079, .010) $p = .818$
Direct debit				.0013 (-.00010, .0028) $p = .067$
Debit card				.00096 (-.00050, .0024) $p = .197$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.430	.430	.430	.430
Observations	37 222	37 222	37 222	37 222

Supplementary Table S50

Predicting whether an individual in the LBG dataset missed payments in months $t = 1$ and $t = 2$ ($0 =$ didn't miss payments; $1 =$ missed payments) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00066 (-.00054, .0018) $p = .280$	.00066 (-.00054, .0018) $p = .280$	.00081 (-.00052, .0021) $p = .232$	.00083 (-.00050, .0022) $p = .222$
Control variables				
<i>What individuals spend</i>				
Month spend		-.0000048 (-.00018, .00017) $p = .957$		
Communication			.013 (-.012, .039) $p = .315$	.013 (-.013, .039) $p = .328$
Financial services			-.000036 (-.00014, .000075) $p = .521$	-.000029 (-.0019, .0013) $p = .720$
Hobbies			.00035 (-.0016, .0023) $p = .728$	.000078 (-.0025, .0026) $p = .952$
Household bills			-.0044 (-.014, .0052) $p = .370$	-.0046 (-.014, .0051) $p = .349$
Miscellaneous			.00032 (-.00059, .0012) $p = .487$	.000061 (-.0018, .0019) $p = .948$
Motor			-.0000029 (-.00083, .00083) $p = .994$	-.00025 (-.0020, .0015) $p = .779$
Retail			.000023 (-.0019, .0019) $p = .981$	-.00019 (-.0022, .0018) $p = .856$
Services			-.00074 (-.0023, .00087) $p = .369$	-.00097 (-.0029, .00098) $p = .329$
Travel			-.00058 (-.0020, .00084) $p = .422$	-.00071 (-.0020, .00067) $p = .314$
Other			.0032 (-.00092, .0074) $p = .127$	-.00094 (-.010, .0087) $p = .848$
<i>How individuals spend</i>				
ATM				.0043 (-.0074, .016) $p = .469$
Direct debit				.00025 (-.0013, .0018) $p = .761$
Debit card				.00027 (-.0012, .0018) $p = .731$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.266	.266	.266	.266
Observations	39 166	39 166	39 166	39 166

Supplementary Table S51

Predicting whether an individual in the LBG dataset missed payments in months $t = 3$ and $t = 4$ ($0 =$ didn't miss payments; $1 =$ missed payments) for mortgages, as a function of their entropy score (1), monthly spend (£'000s) (2), spend by merchant category (£'000s) (3), and spend by channel usage (£'000s) (4). All models include individual fixed-effects.

Independent variable	(1)	(2)	(3)	(4)
Entropy (1 month)	.00076 (-.00063, .0021) $p = .286$	.00075 (-.00064, .0021) $p = .290$	.00085 (-.00068, .0023) $p = .277$	.00082 (-.00070, .0023) $p = .291$
Control variables				
<i>What individuals spend</i>				
Month spend		-.000065 (-.00032, .00019) $p = .624$		
Communication			.0014 (-.022, .025) $p = .902$	.0023 (-.021, .026) $p = .845$
Financial services			.000020 (-.00011, .00015) $p = .765$	.00099 (-.0019, .0039) $p = .505$
Hobbies			-.0028 (-.0056, .000034) $p = .052$	-.0020 (-.0059, .0019) $p = .322$
Household bills			.0025 (-.0070, .012) $p = .598$	.0033 (-.0062, .012) $p = .495$
Miscellaneous			-.00032 (-.0011, .00045) $p = .418$	.00060 (-.0024, .0036) $p = .695$
Motor			-.000069 (-.00092, .00078) $p = .872$	.00069 (-.0021, .0035) $p = .636$
Retail			.00061 (-.0020, .0033) $p = .656$	.0012 (-.0030, .0056) $p = .569$
Services			.00068 (-.0019, .0032) $p = .608$	.0014 (-.0018, .0046) $p = .398$
Travel			-.0000030 (-.0011, .0011) $p = .995$	.00040 (-.0013, .0021) $p = .659$
Other			-.0015 (-.0063, .0032) $p = .535$	.0021 (-.0036, .0080) $p = .458$
<i>How individuals spend</i>				
ATM				-.0038 (-.010, .0029) $p = .269$
Direct debit				-.0010 (-.0039, .0018) $p = .482$
Debit card				-.00082 (-.0037, .0021) $p = .587$
Individual fixed-effects	Yes	Yes	Yes	Yes
R^2	.188	.188	.189	.189
Observations	39 164	39 164	39 164	39 164