Personal Financial Transactions (aka Open Banking): Opportunities and Challenges for Research

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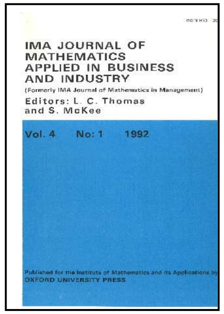
CRC Credit Research Centre

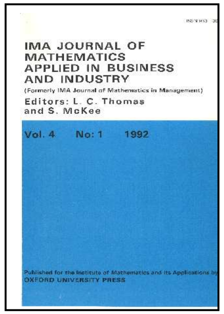
The [Credit Research Centre (CRC)](#) is an impartial independent research group devoted to the study of credit

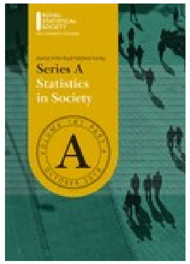
- Founded in **1997**
- Successful collaboration with the industry and regulations since **1989** (1st Credit Scoring & Credit Control conference)
- **20th** conference - Edinburgh 31 August to 03 September 2027
- Seminar and webinar series, Village Hall discussions, working papers, and much more.

The last conference was attended by 430 delegates from162 organisations (Universities, financial institutions, Central Banks) and from 41 countries

13 Special Issues + 5 Impact Case Studies





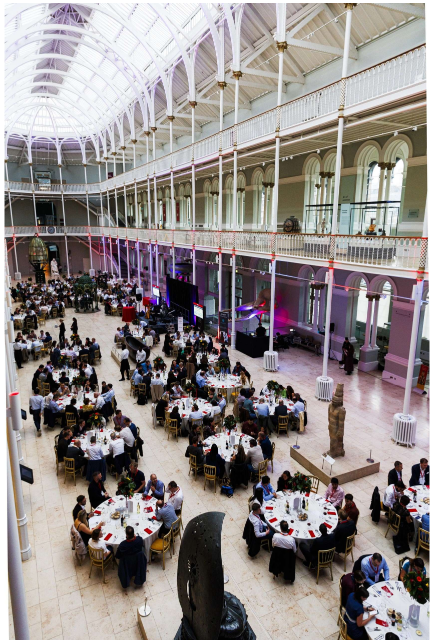


Credit Scoring & Credit Control conference

The 20th conference - Edinburgh 31 August to 03 September 2027

Last conference in 2025:

- 430 delegates from 162 organisations (20% academics, 80% practitioners),
- 41 countries: US to Cambodia and Iceland to South Africa,
- 9 commercial sponsors,
- Over 100 competitively selected papers in 5 streams,
- Special Edition of Springer's Banking & Finance series.



Summary

- High-level overview of CRC research on Open Banking with the focus of Financial Vulnerability
- Definitions, what is Open Banking, sources of data for analysis
- Open Banking (OB) as an example of Big Data, categorisation
- Early exploratory analysis
- Paper 1: Power of OB data: Financial Vulnerability (FV) profiling
  - Revealing too much? Is there connection to protected characteristics?
  - What if someone wants to target a vulnerable group?
- Paper 2: FV stages - defining threshold levels
- Further directions, including Consumer Duty.

Open Banking/ transactional data

- The second Payment Services Directive (PSD2 or Open Banking in the UK) is a game changer in retail finance. It enables easier access to dynamic, real-time consumer data in practice, with bank transaction data being of particular interest.
- The motivation behind PSD2 is to facilitate better flow of financial information and through this, improve financial inclusion.
- Open Banking is often used as a synonym for current account transactions, and this is the case with this presentation.
- Current accounts form the core of OB, real example of Big Data, providing new challenges.
- So far good progress with transactions categorisation - a pre-cursor to any analysis; has been successfully dealt by the industry.

Sources of Open Banking

Aggregators or money management apps, e.g. MoneyHub, Money Dashboard

- Examples: Lukas & Howard (2023)
- Advantages:
  - Provides a comprehensive picture of individual finances;
  - Good for experimental research.
- Disadvantages:
  - Relatively low coverage of the general population, skewed towards younger and financially savvy segments.

Current Accounts

- Examples: all papers in this presentation, data from three different sources.
- Advantages:
  - Provides a comprehensive coverage of the general population
  - Good for analysing general trends and behaviours.
- Disadvantages:
  - May miss elements of financial status/ behaviour, although can still see payments to savings and credit accounts.

Financial Vulnerability

Joint work with Professor Tina Harrison, sponsored by Salad Holdings

"Thousands of NHS workers have been left heavily reliant on several high-cost loans charging interest of up to 1,333% because they are being excluded from more affordable mainstream options, a new report claims.

The study by researchers from the University of Edinburgh Business School examined the finances of almost 10,000 mainly lower-paid and younger NHS workers, and found that almost a third (30%) were using five or more loan providers, many of which were high-cost, such as payday and short-term loan firms."

The Guardian, 21.02.2021

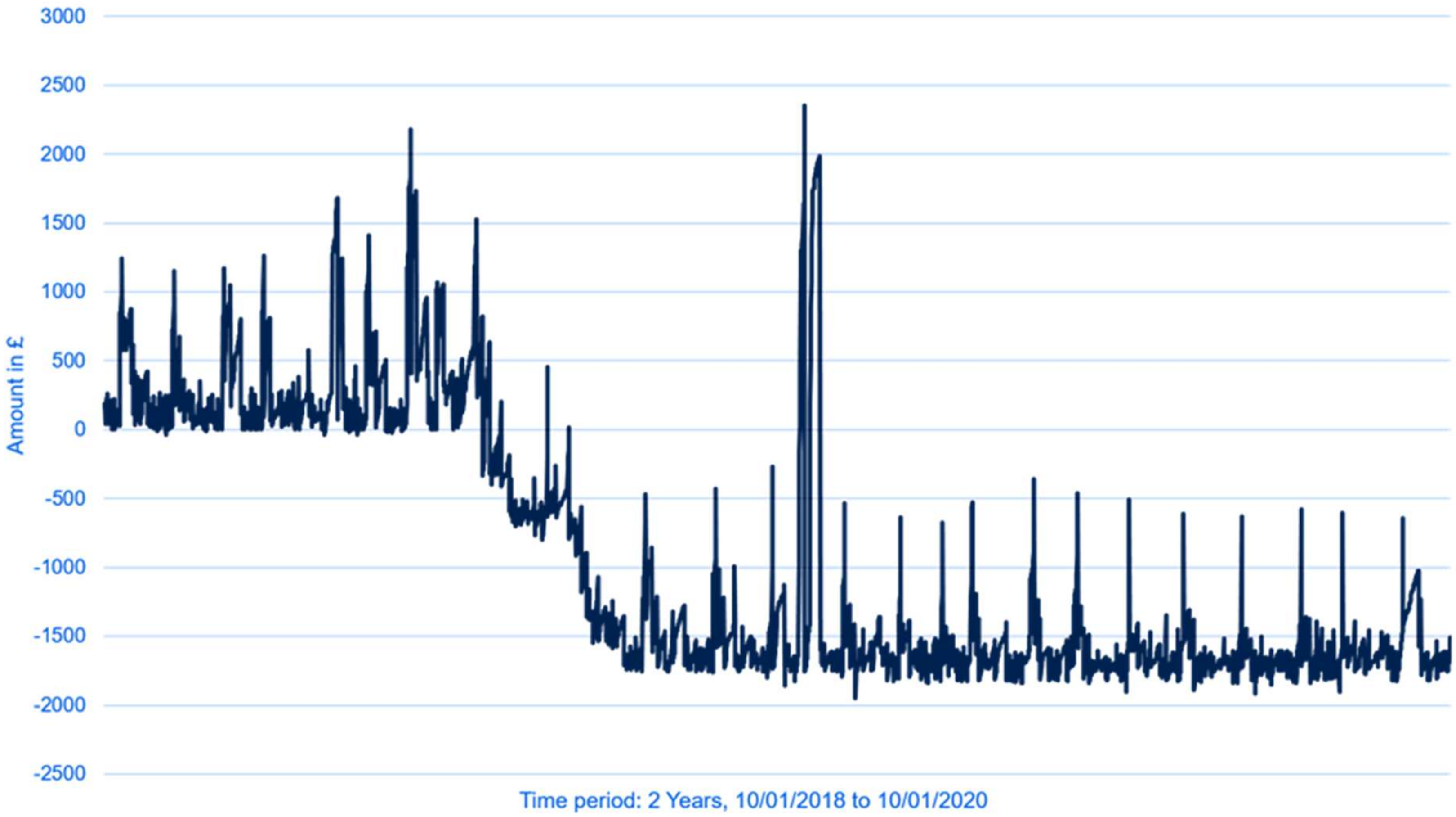
More information:
Harrison & Andreeva (2021) 'Financial Health of NHS Workers' Report 1

Harrison, Andreeva, Garzon-Rozo & Zhang (2022) 'Financial Resilience and Credit Landscape of Public Sector Workers' Report 2

What you can and cannot see from OB

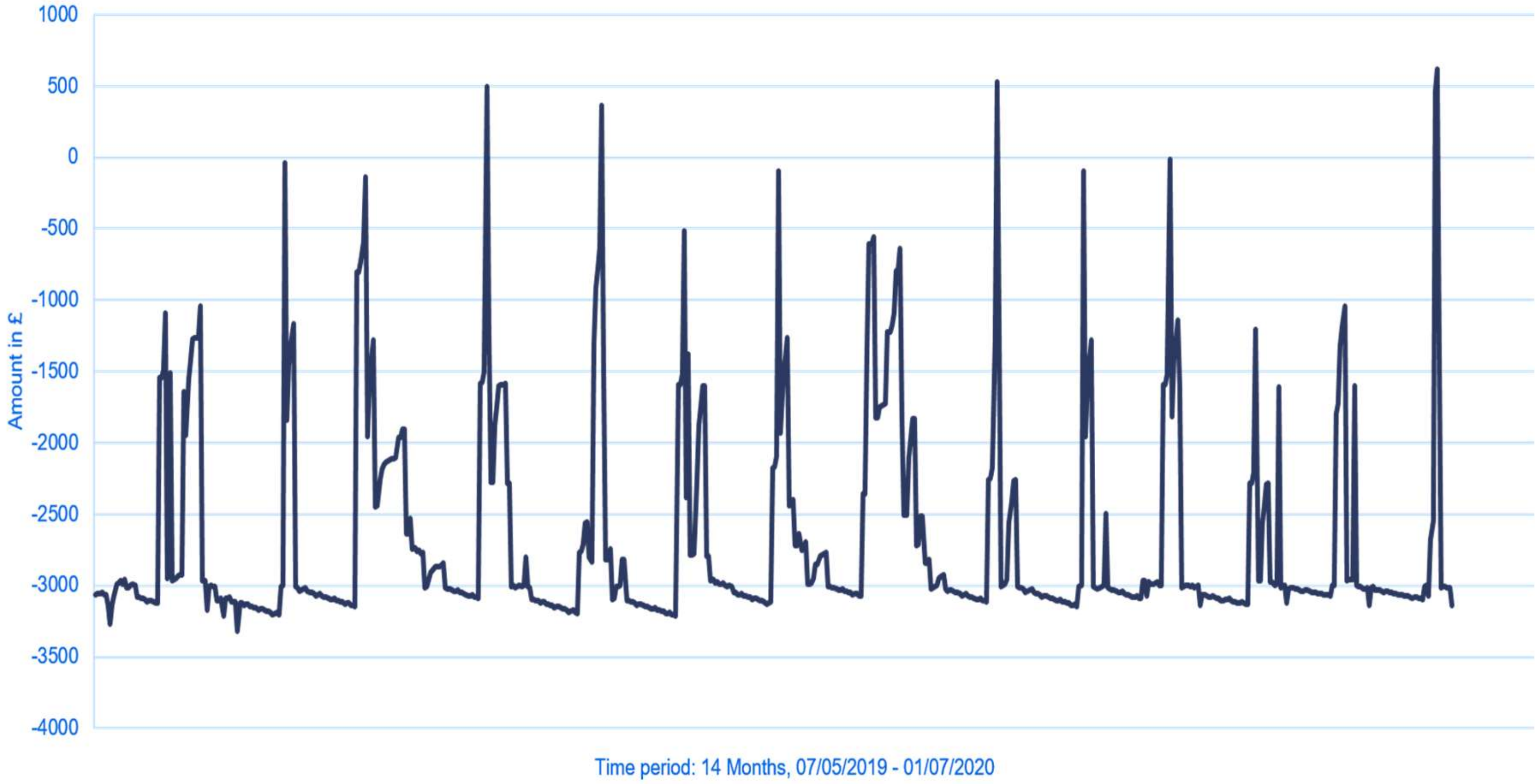
- Very granular and detailed individual patterns in income and spending.
- Sources of income: salaries, benefits, internal transfers.
- Types of expenditure: depends on categorization, yet normally regular commitments (mortgage, rent, credit repayments), essential spending (food), non-essential (eating out).
- Can trace dynamics of income/expenditure and overall financial status.
- Can analyse addictive or harmful behaviour: gambling, compulsive shopping, sinking into credit trap.
- But bank transfers are often impossible to categorise.
- Cannot see the shopping bill, only the name of retailer.
- Cannot see credit or investment terms.

Individual account balance example 1



Source: Report 1

Individual account balance example 2



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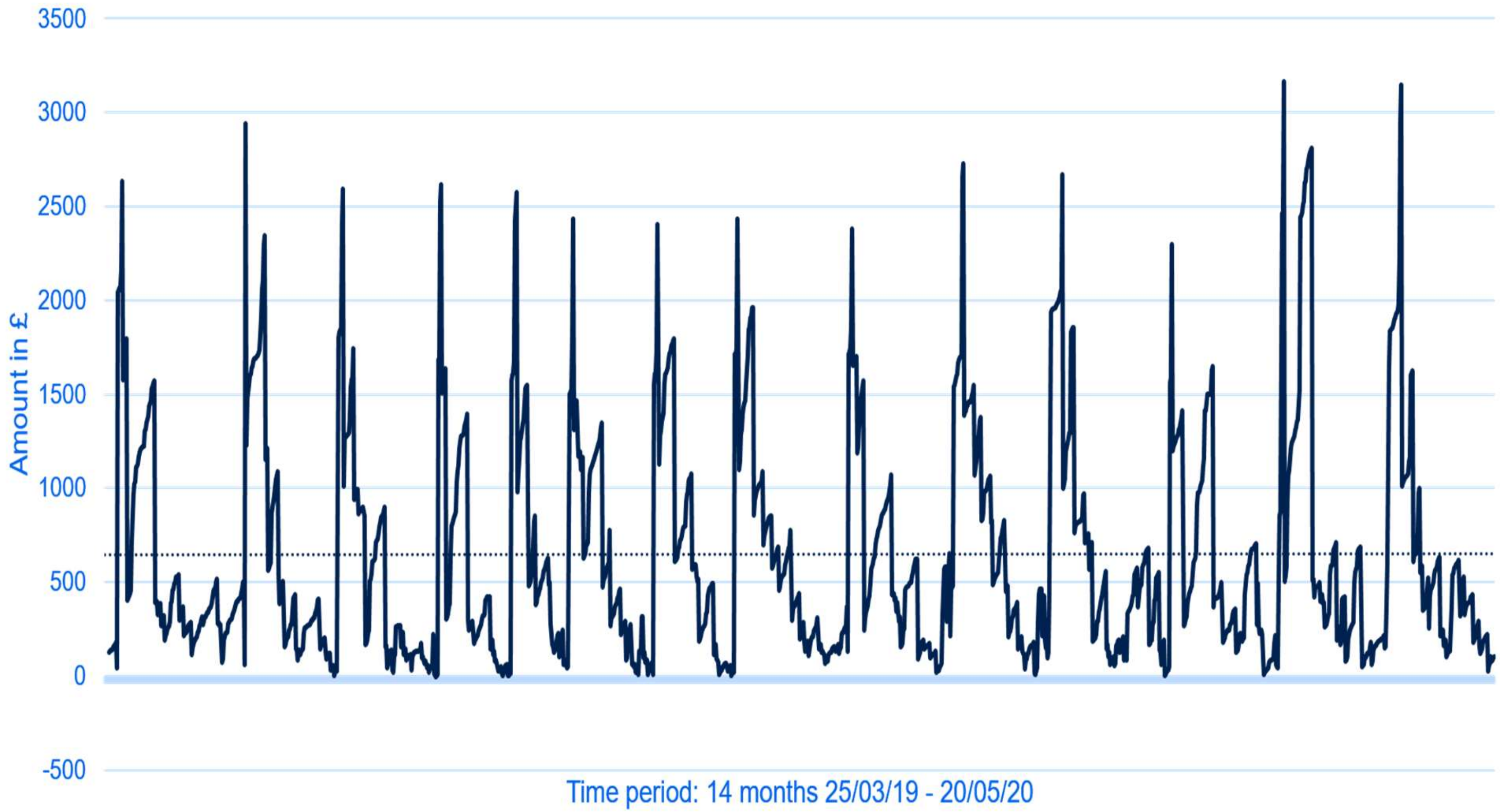
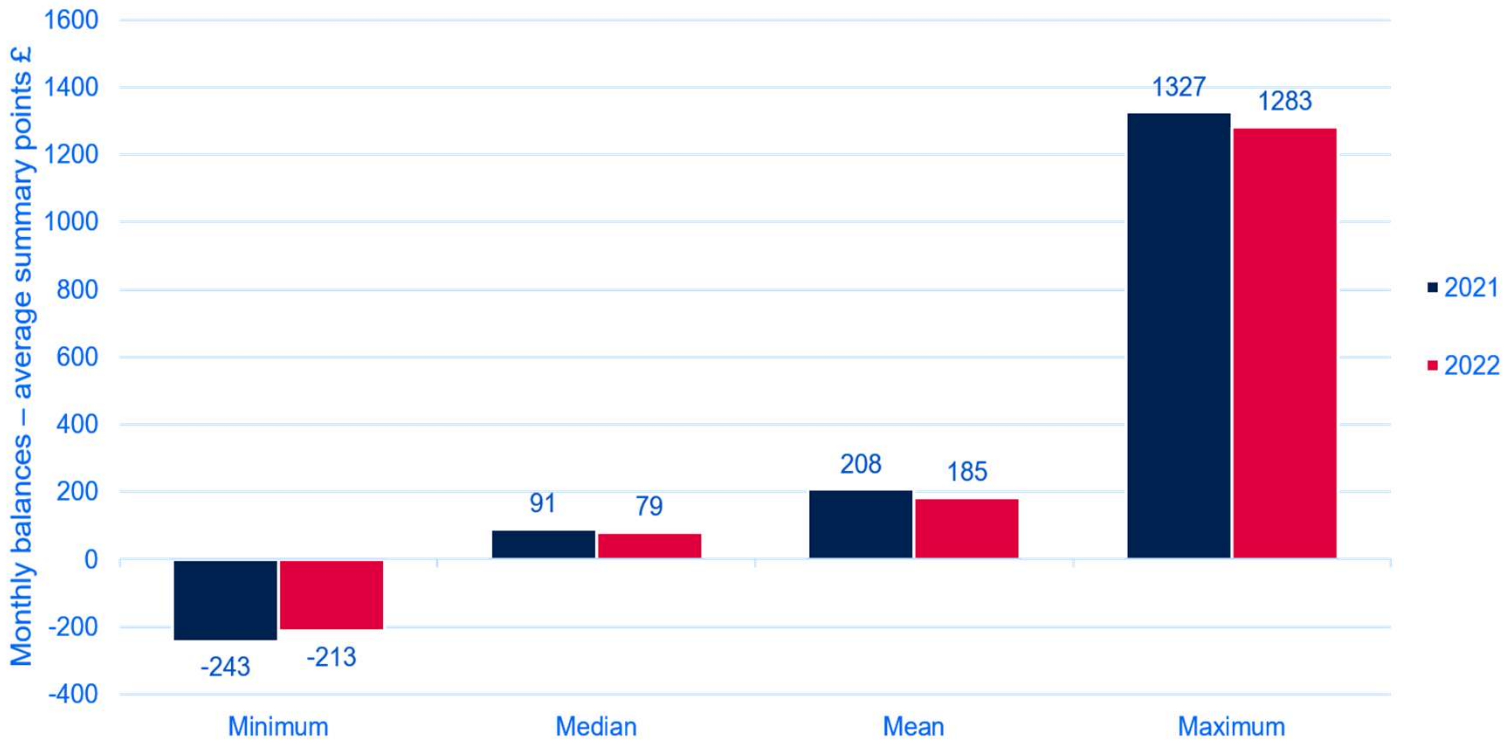
Individual account balance example 3



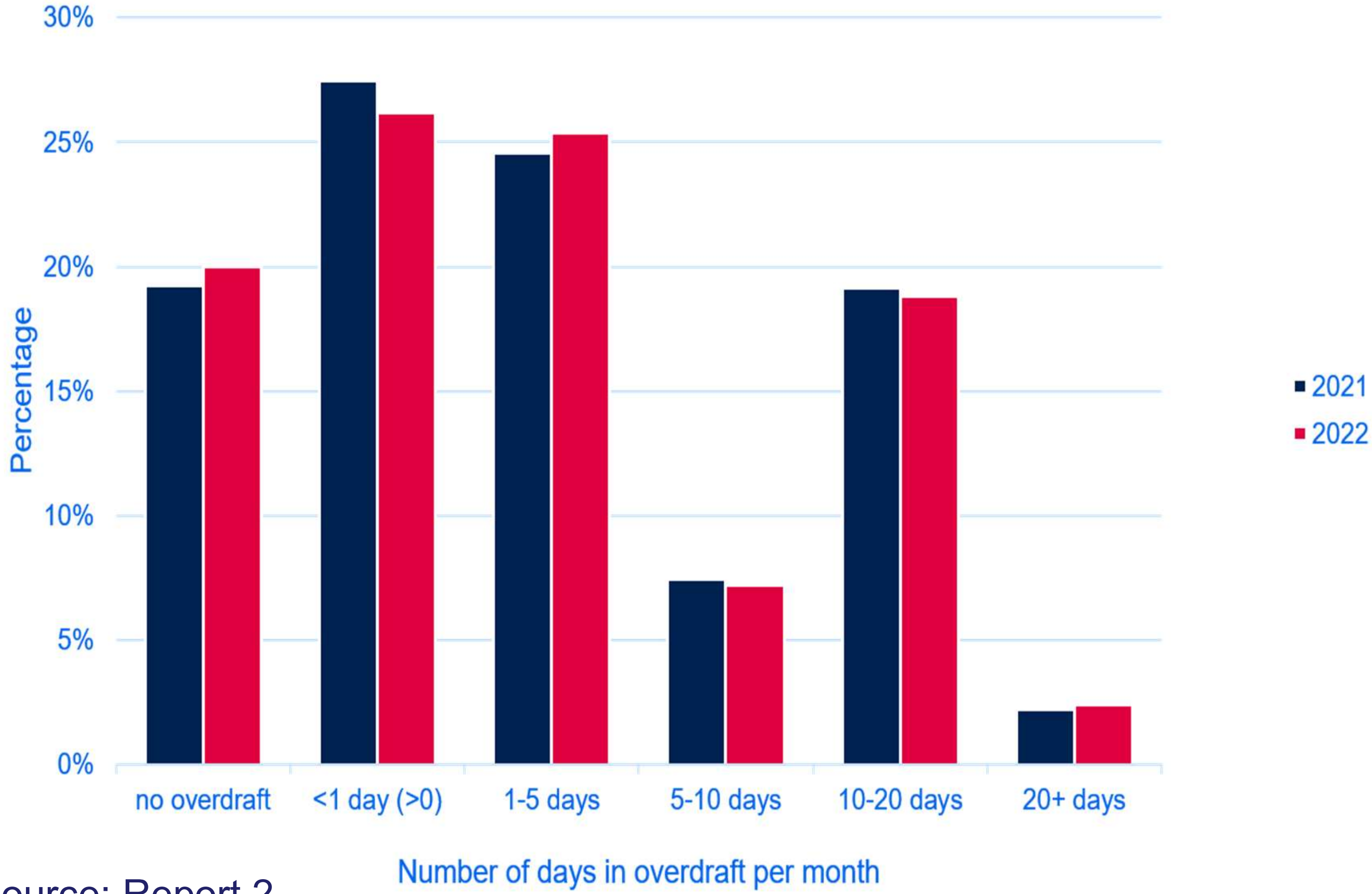
Source: Report 1

What summary measures to use



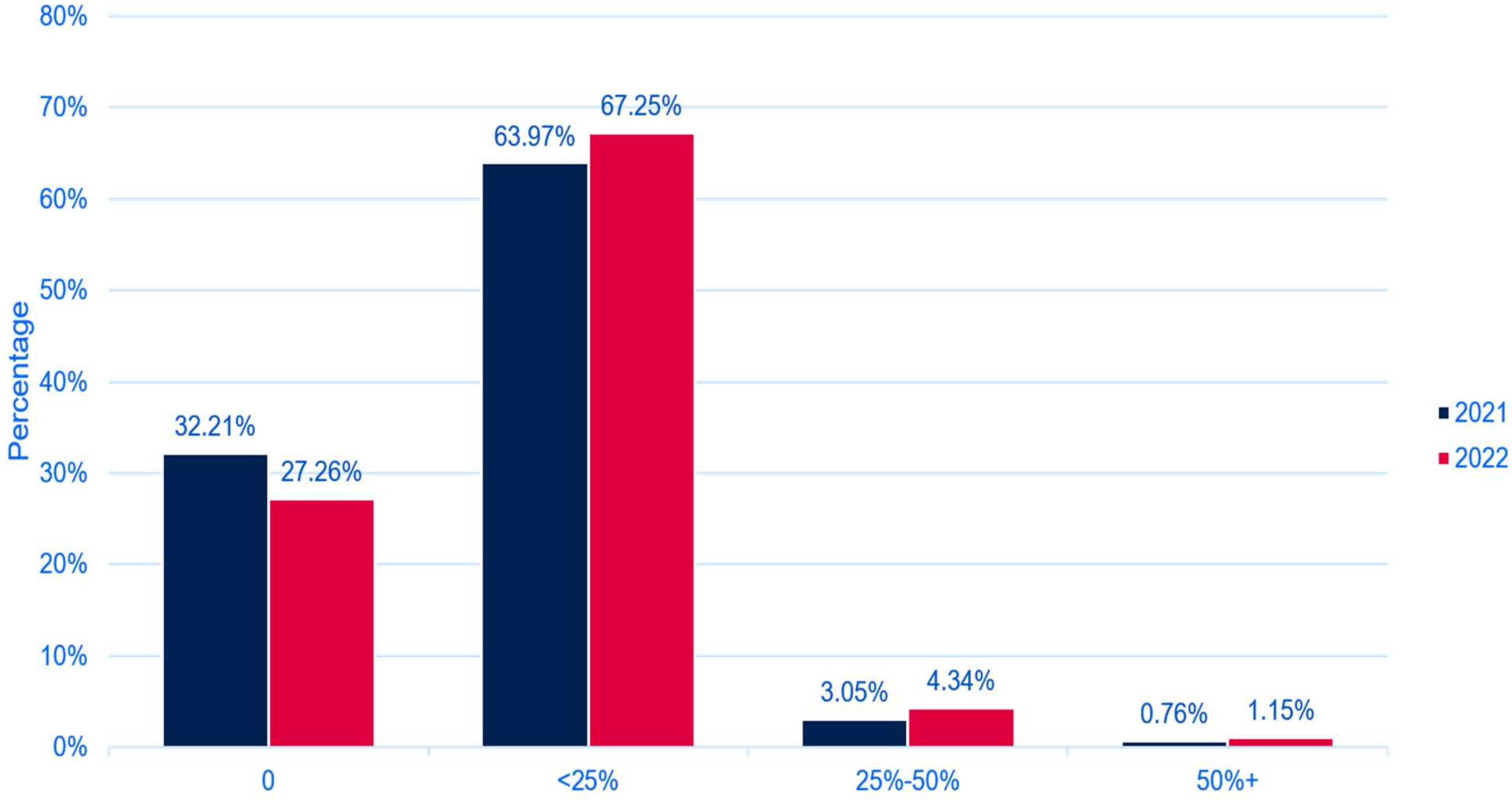
Source: Report 2

Overdraft use



Source: Report 2

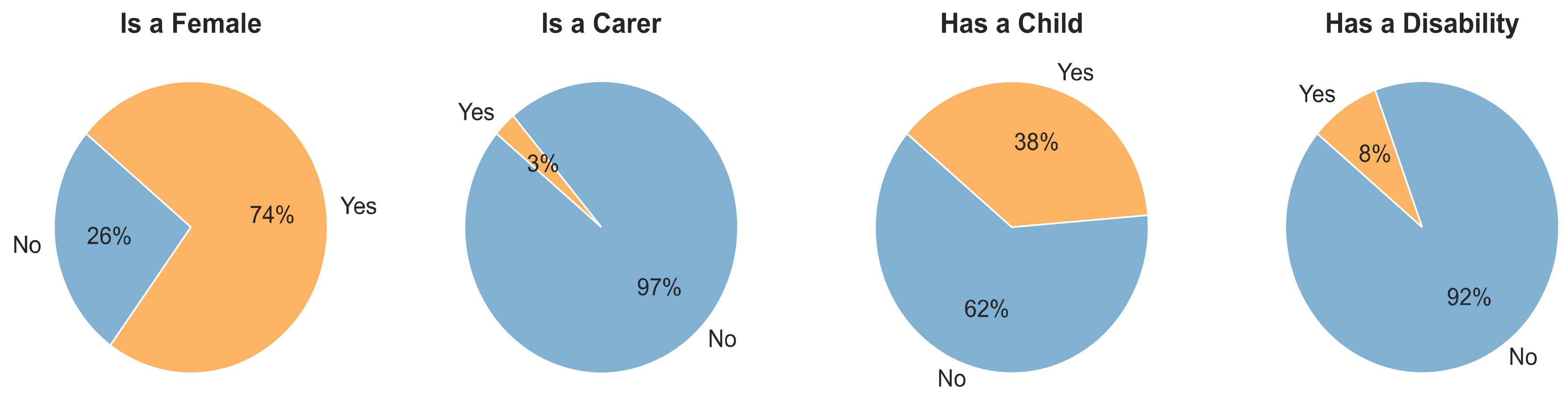
Gambling expenditure as a % of total annual outgoings

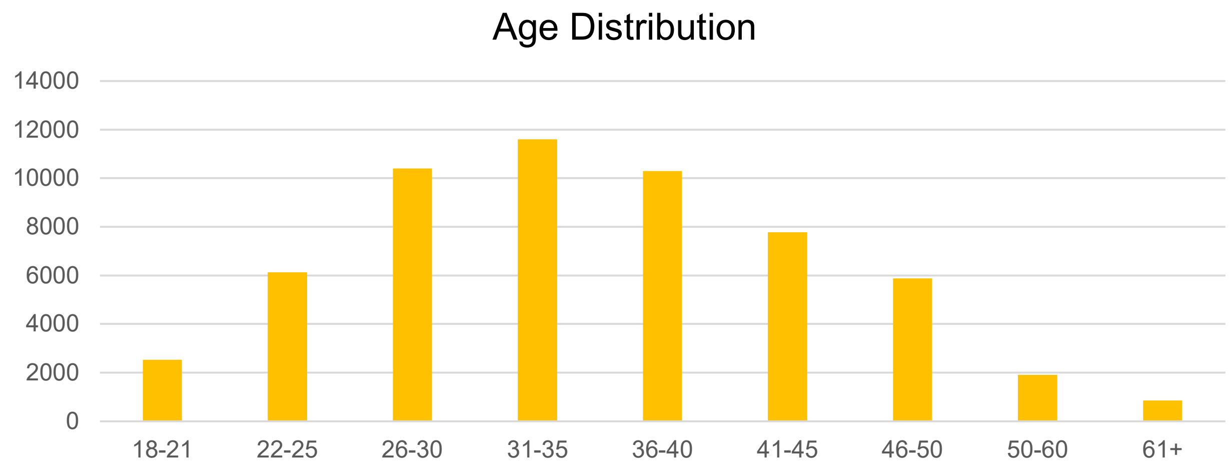


Source: Report 2

Is OB revealing too much?

Protected and sensitive attributes





Kim, S., Andreeva, G., & Rovatsos, M. (2023).

Legal position

The Law makes the distinction between direct and indirect discrimination.

It is concerned with procedural fairness or ‘**equal treatment**’ or ‘direct discrimination’ which is strictly prohibited → certain variables cannot be used as inputs into a model (be it a regression or a machine-learning algorithm).

The public and media seem to be more concerned about outcome fairness or ‘**equal outcome**’. However, unequal outcomes can arise from ‘indirect discrimination’, where an apparently neutral criterion would put persons of a particular group (e.g. gender) at a disadvantage compared with other persons. This can be justified by a legitimate aim, given the means of achieving that aim are appropriate and necessary.

Equal treatment does not automatically result in equal outcome, see Andreeva, G., Matuszyk, A.: The law of equal opportunities or unintended consequences: The impact of unisex risk assessment in consumer credit. Journal of Royal Statistical Society, Series A, 182(4), 1287—1311 (2019)

Financial Vulnerability definition

There is no official or universally accepted definition of FV. In the UK much of existing conceptual work has been linked to Financial Conduct Authority's (FCA) seminal work, which includes qualitative explorations and the development of the Financial Lives survey (FCA, 2017, 2021). We follow the FCA definition and guidance: "A vulnerable customer is someone who, due to their personal circumstances, is especially susceptible to harm, particularly when a firm is not acting with appropriate levels of care" (FCA, 2021, p.3).

According to FCA, key indicators of being 'financially in difficulty' or having 'low financial resilience' include having **insufficient funds in their account, being over-indebted, having low or erratic incomes** or **low savings** and being **unable to withstand an unexpected increase in monthly expenses** such as rent.

Financial Vulnerability indicators/ binary target variables

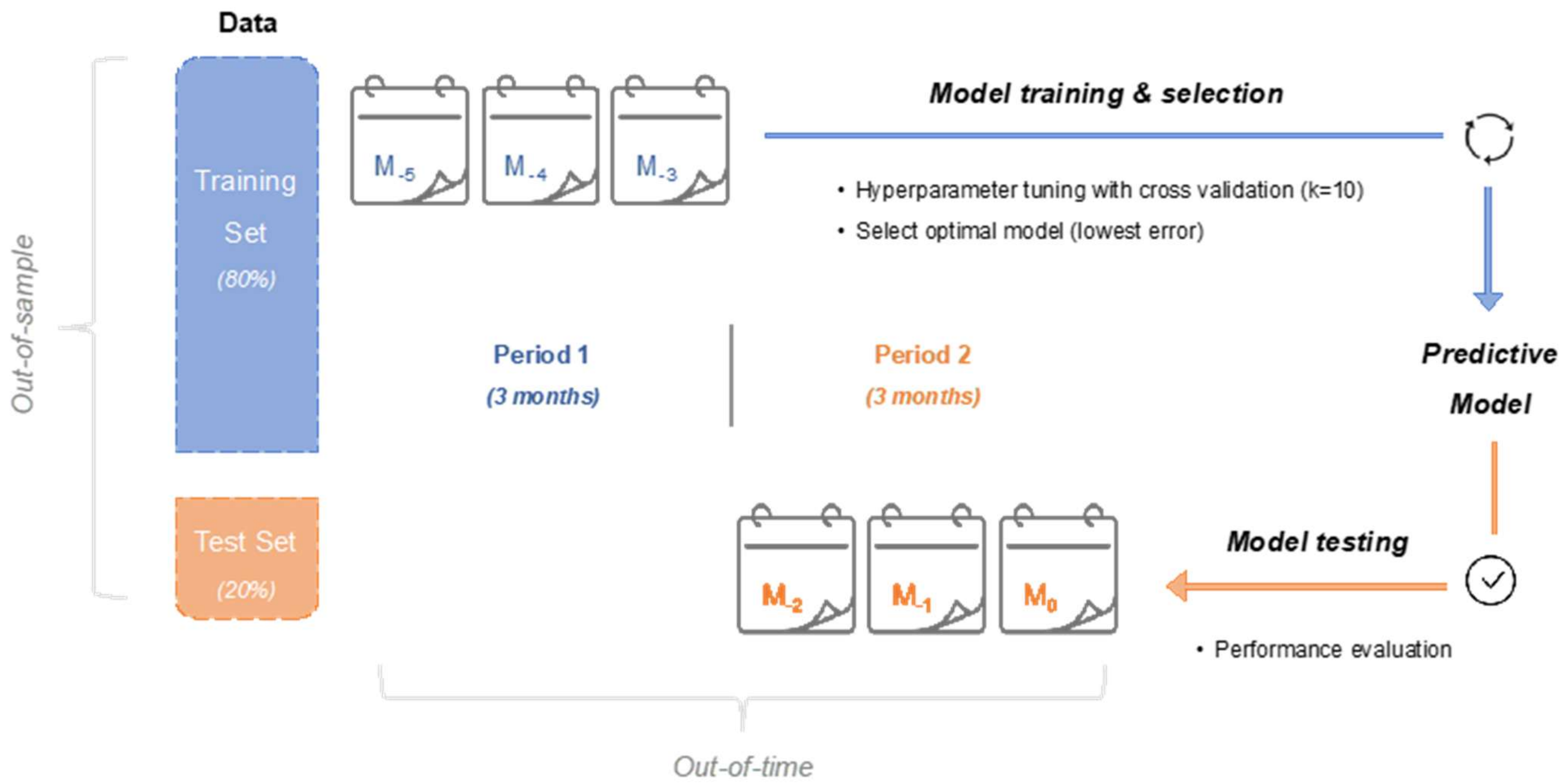
1. *Financial shock withstanding* (48.3% of applicants): average median monthly balance below £100.
2. *Insolvent* (4.0%): payments to *debt management and insolvency companies*.
3. *Insufficient disposable income* (11.6%): average monthly disposable income is less than £100.
4. *Overdraft* (67.4%): one or more days in overdraft (OD) per month for more than 50% of the months throughout their account history.
5. *Returned direct debits* (28.3%): When an applicant has at least one or more returned direct debits (RDD), insufficient funds resulting in a rejection of a pre-arranged payment by the bank.
6. *Gambler* (20.2%): £100 or more on average per month spent on gambling.

Financial behaviours/predictors

Over 100 variables, examples include:

- Financial Management:
  - Inflow (e.g. Total Income, # of income sources, consistency)
  - Outflow (Expenditure by category: housing, groceries, health, gambling)
  - Volatility (**Burstiness in spending**)
- Financial Distress (Debt management payments, overdraft, RDD)
- Financial Resilience (Account Balance, Disposable Income)
- Financial Planning (Insurance, Savings)
- Financial Aid (Total Benefits, Amount by Benefit Types, Pensions)
- Financial Inclusion (# credit providers, # cards, loans, payday loans).

Modelling


Data
Training Set
(80%)
Test Set
(20%)
Out-of-sample
M-5
M-4
M-3
Model training & selection
• Hyperparameter tuning with cross validation (k=10)
• Select optimal model (lowest error)
Period 1
(3 months)
Period 2
(3 months)
Predictive Model
M-2
M-1
M0
Model testing
• Performance evaluation
Out-of-time

Correlations

		Profile			Benefits Received			Financial Vulnerability Indicators				
		Age	Employment Length	Female	Carer	Child	Disability	Financial shock	Gambling expenditure	Insolvency & DM	Disposable income	Over-draft
Profile	Employment Length	0.269**										
	Female	0.043	-0.014									
Benefits Received	Carer	-0.001	-0.030	0.038								
	Child	-0.010	0.028	0.362**	0.095**							
	Disability	0.073**	0.011	0.078	0.334**	0.131**						
Financial Vulnerability Indicators	Financial shock withstanding (% of months)	0.182**	0.089**	0.033	0.007	0.053**	0.060**					
	Gambling expenditure (£)	-0.004	0.036	-0.116**	0.008	-0.045**	0.001	0.101				
	Insolvency & debt management expenditure (£)	0.096	0.072	0.008	-0.017	0.022	-0.003	0.103	0.001			
	Disposable income (£)	0.015*	0.027	-0.006	0.043	0.053**	0.051	0.059	0.403**	0.031		
	Overdraft (% of months)	-0.077	-0.014	-0.004	-0.019	0.024	-0.014*	-0.586**	-0.009	-0.026	-0.030	
	No. of returned direct debits	-0.025	-0.043	0.041	0.031	0.088**	0.047	-0.163**	0.025	0.049	0.059	0.332**

Predictive accuracy

		AUROC	
		Mean	*Std*
Withstand financial shock	*LR*	0.756	0.007
	RF	0.903	0.004
	XGB	0.895	0.004
Gambler	*LR*	0.875	0.006
	RF	0.893	0.006
	XGB	0.911	0.006
Returned Direct Debits	*LR*	0.775	0.005
	RF	0.870	0.004
	XGB	0.884	0.004

		AUROC	
		Mean	*Std*
Has a Child	LR	0.824	0.006
	RF	0.917	0.003
	XGB	0.917	0.004
Has a Disability	LR	0.796	0.018
	RF	0.885	0.010
	XGB	0.864	0.010
Female	LR	0.832	0.004
	RF	0.896	0.003
	XGB	0.917	0.002

LR=Logistic regression, RF = Random Forest, XGB = eXtreme Gradient Boosting evaluated with the Area Under the Receiver Operating Characteristic Curve (AUROC), higher values → better predictions.

Impact on protected and sensitive groups

		Acceptance Rate			
		Withstanding financial shock always		No Returned Direct Debits	
		PA Excluded	*PA Included (delta)*	*PA Excluded*	*PA Included (delta)*
Gender	Female	21.4%	0.0%	20.4%	0.0%
	Male	16.1%	0.1%	18.9%	-0.1%
	Male & no benefits	14.4%	-0.3%	18.7%	-0.1%
Benefit	Is carer	25.5%	-0.1%	16.9%	-0.1%
	Has child	23.9%	0.0%	18.7%	0.0%
	Has disability	29.4%	-1.1%	17.7%	-0.1%
Intersectionality	Female & has child	23.5%	0.0%	18.5%	-0.1%
	Female & has disability	31.1%	0.1%	18.1%	0.3%
	Female & is carer	25.7%	-1.4%	16.7%	-0.1%
	Has child & disability	32.9%	-1.5%	16.3%	0.2%
	Has child & is carer	29.4%	0.0%	15.0%	0.2%
	Is carer & has disability	32.0%	0.5%	15.8%	0.2%
Age	Age: 18-21	5.1%	1.2%	16.9%	0.0%
	Age: 22-25	7.2%	0.9%	15.1%	-0.1%
	Age: 26-30	13.1%	1.1%	17.0%	0.3%
	Age: 31-35	18.6%	0.3%	18.1%	0.2%
	Age: 36-40	24.2%	-0.1%	20.1%	0.0%
	Age: 41-45	24.7%	-0.8%	22.2%	0.1%
	Age: 46-50	28.3%	-1.2%	23.3%	0.0%
	Age: 51-55	30.0%	-1.6%	27.2%	-0.8%
	Age: 56-60	32.6%	-1.3%	28.0%	-1.0%
	Age: 60+	30.4%	-0.2%	29.1%	-1.5%

Simulating a scenario, where a lender accepts 20% of applicants, based on the higher probability of e.g. No RDD. Equal outcome would mean 20% acceptance rate across all the subgroups.

Some thoughts

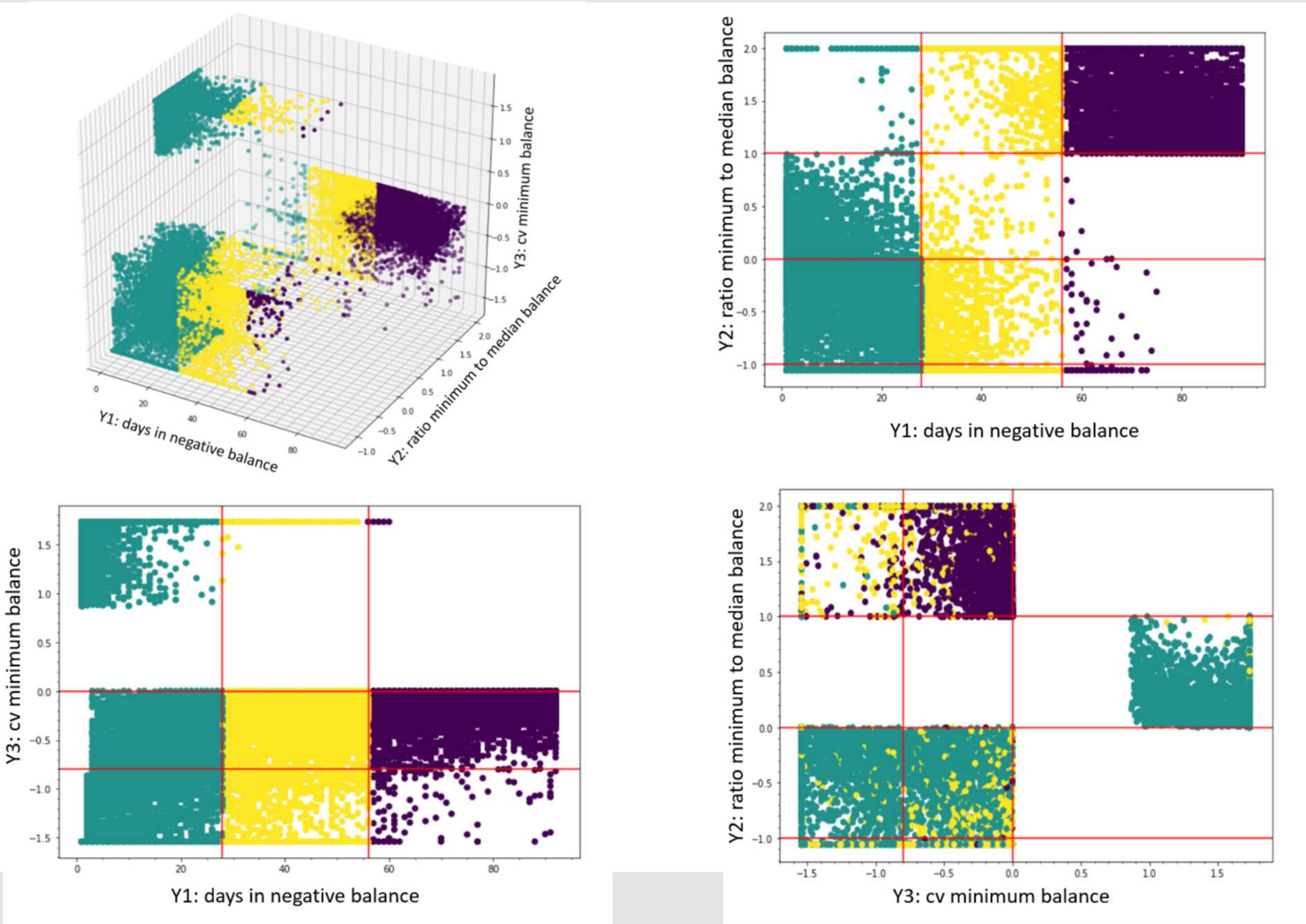
- We demonstrated the power of OB and AI/ML in profiling the vulnerable customers.
- Good use: e.g. to take early actions to improve the customer's situation.
- Bad use: e.g. targeting vulnerable consumers by predatory lenders.
- Recommendation 1: ensure that powerful data and technology benefits the customers.
- Need to be aware of hidden associations with protected and sensitive attributes.
- Recommendation 2: guidance on dealing with these associations.
- Intersectionality is another big topic that requires attention and research.

Is FV more complex than binary?

- Examine overdraft, since negative balances indicate a deficit, essentially borrowing from the bank. Similar to credit scoring, where credit default is measured by the number of days past due and the overdue amount.
- Three dimensions:
  1. number of days in a negative balance ($Y1$),
  2. ratio of average minimum balance to average median balance ($Y2$),
  3. fluctuations in minimum balance ($Y3$), quantified using the coefficient of variation (CV).
- Define the observed states of overdraft use through hierarchical clustering with $Y1$, $Y2$ and $Y3$; visualise these groupings in a 3D space (top-left figure, next slide) and refine cut-off points in two-dimensional spaces.
- Use Hidden Markov Chain to reveal the stages of FV as a latent construct.

Goh, R., Andreeva, G., & Cao, Y. (2024).

Observed OD states



Latent FV states

- Used 16 X variables, describing various aspects of financial behaviours. Following 4 main dimensions by FCA: (1) low financial resilience, (2) negative life events, (3) poor health, (4) low capability.
- Applied extended multivariate latent Markov (LM) model, which incorporates covariates that influence the latent distribution (Bartolucci et al. 2017).
- The number of latent states (k) is not known in advance, estimate k = [2, 5]. AIC/BIC criteria favour k = 3 as the best representation of the data.
- The paper analyses (i) the characteristics of these latent states, (ii) the distribution of the latent process to understand transitions between states, (iii) the influence of covariates on the latent distribution, and (iv) the prediction of state sequences for new accounts.
- This approach offers a potential way to propose data-driven definitions.

Goh, R., Andreeva, G., & Cao, Y. (2024).

Latent FV states, emission probabilities

Observed target variables	Category	Latent states 1	2	3
$y1$: Days in negative balance				
0: $y1 = 0$	0	0	**0.9133**	0
1: $1 \leq y1 < 28$	1	**0.7741**	0.0841	0
2: $28 \leq y1 < 56$	2	0.2254	0.0023	0.2454
3: $y1 \geq 56$	3	0.0005	0.0004	**0.7546**
$y2$: Ratio of minimum to median balance				
0: $y2 < -1$	0	0.2957	0	0.0743
1: $-1 \leq y2 < 0$	1	**0.6625**	0	0.0033
2: $0 \leq y2 \leq 1$	2	0.0008	**1**	0.0208
3: $y2 > 1$	3	0.0410	0	**0.9017**
$y3$: Minimum balance CV				
0: $y3 < -0.80$	0	**0.6142**	0	0.0400
1: $-0.80 \leq y3 < 0$	1	0.3811	0	**0.9324**
2: $y3 > 0$	2	0.0047	1	0.0276

Goh, R., Andreeva, G., & Cao, Y. (2024).

Further projects

Other useful applications of OB, e.g. identifying money-laundering through suspicious activities, e.g. “shell” accounts. Model typical vs atypical behaviour, Outlier score to rank the risk.

Investigating income volatility, linking it to macroeconomics and identifying customers that are most vulnerable depending on certain scenarios.

Consumer Duty implies a unified framework and effective benchmarking, which requires a set of standardised, comparable measures. “Developing Standardised Measures for Consumer Duty Compliance, Affordability and Competitiveness in Consumer Lending” (Report 3) analyses the existing measures/concepts and the existing gaps.

1. Fair Value: Definitions of fairness must be clarified and assessed at three levels: perceived fairness by customers, fairness metrics by lenders (e.g., price-to-cost/risk analysis), and fairness across the industry via benchmarking.

2. Financial Inclusion and Competitiveness: Bureau credit scores may serve as proxies but require further validation. Alternatives must be developed for financially excluded customers.

3. Relending and Persistent Use: Evaluating firms’ reliance on relending requires qualitative assessments of business models and quantitative tracking of customer journeys using OB and credit bureau data.

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