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Consumer behaviour and credit supply: Evidence from an Australian FinTech lender

Mingze Gao, Henry Leung *, Linhui Liu, Buhui Qiu

The University of Sydney Business School, University of Sydney, NSW, 2006, Australia

A R T I C L E I N F O

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A B S T R A C T

Using a proprietary dataset from an Australian leading FinTech lender, we provide insights into the effect of consumer behaviour on FinTech lending patterns. Out of seven consumption categories, gambling expenses significantly reduce the lender's willingness to fulfill loan requests. Cash usage and repeated borrowing are related to lower offer-to-requested loan ratios. The FinTech lender prefers to lend to borrowers who are married, have dependents and/or aged over 30. However, for such mature borrowers, cash usage and repeated borrowing increasingly reduce the approval likelihood of their loan requests. Taken together, our empirical evidence suggests that consumer behaviour affects FinTech lending decisions.

1. Introduction

In this study, we provide new evidence on the relationship between consumer behaviour and credit access using a novel data by a leading Australian FinTech lender specialized in short-term consumer credit products. FinTech firms have garnered increasing attention amongst policy makers and regulators given its disruption to how traditional businesses are conducted in the consumer credit market, particularly through open banking initiatives. Jagtiani and Lemieux (2019) show that FinTech lenders utilize more soft information from alternative data sources in screening and this business process benefits borrowers who would otherwise be unable to obtain credit. Di Maggio and Yao (2021) investigate FinTech lenders' pricing strategies and borrower outcomes using a large dataset on household balance sheets. They find that FinTech lenders rely on hard information from credit reports rather than soft information or alternative data.

We contribute to this growing literature by presenting novel evidence on how soft information from bank statements surrounding payment and consumption behaviours affects the willingness of FinTech lenders to fulfill loan requests. Prior studies have shown some alternative data, such as applicant's appearance, social network and writing style, etc., used in FinTech lending (e.g., Herzenstein et al., 2011; Lin et al., 2013; Gonzalez and Loureiro, 2014; Dorfleitner et al., 2016; Freedman and Jin, 2017; Buchak et al., 2018; Jiang et al., 2018; Croux et al., 2020). Our unique dataset allows us to show that FinTech lender's willingness to supply credit depends on the consumer behaviour revealed from information contained in bank statements and applicant demographics. Moreover, to the best of our knowledge, we are amongst the first to study the effect of consumer behaviour on FinTech lending, while most extant studies focus on the implications of FinTech lending on borrowers (e.g., Gathergood et al., 2019; Di Maggio and Yao, 2021) or the prediction of defaults (e.g., Khandani et al., 2010).

Specifically, we employ a proprietary approved loan dataset from an Australian leading FinTech lender specializing in short-term

* Corresponding author.
E-mail address: henry.leung@sydney.edu.au (H. Leung).

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consumer credit products, whose business model relies on machine learning and artificial intelligence to screen loan requests. Potential applicants submit applications online and grant the lender access to their recent bank statements, which allows the lender to directly observe transaction-level consumption behaviour. The lender either rejects the application or responds with customized loan offer in terms of loan amount, maturity and interest rate, which the applicant can subsequently accept or not. This whole process can be completed within minutes to a few hours and is far more efficient than traditional lending channels. Importantly, our dataset explicitly captures aspects of soft information that extant studies cannot, such as utility and rent repayments, records of withdrawal transactions, insurance spending and others (Jagtiani and Lemieux, 2019). This dataset further allows us to differentiate the applicant's requested loan amount and the lender's offered amount, which enables us to measure the lender's willingness to supply credit using a continuous ratio of offer-to-requested loan amount. In the dataset, bank transactions are aggregated into seven categories including gambling, grocery, utility, transportation, insurance, TV subscription and telecommunication expenses. We also observe ATM withdrawals as a proxy for cash usage in addition to typical loan and borrower characteristics. We apply a fixed effects linear regression model to investigate the relationship between applicant's consumer behaviour and credit supply.

We conjecture that FinTech lenders use more than hard information such as the applicant's credit score and prior defaults from credit reports in its lending decision and base its lending decision on additional soft information such as applicant characteristics that comprises consumption patterns and payment preferences. While we are ex-ante unclear about which types of consumption are positively or negatively associated with the lending decision, we expect more cash usage to be adversely related to the lender's willingness to fulfill applicant's loan requests. This conjecture is motivated by Ghosh et al. (2021), who document an adverse impact of large share of cash payments on loan approval due to the untraceable and unverifiable nature of cash usage. Moreover, while past lending relationship helps to mitigate information asymmetry, lenders can also hold up repeated borrowers, charging a higher markup and/or offering smaller loans. Though largely an empirical question, given that our focus is a short-term credit provider, we expect that repeated borrowing is negatively associated with lender's supply of credit. A full development of the literature and hypotheses are presented in Appendix A.

After controlling for a wide range of known factors in lender screening process, we find that the lender indeed relies on soft information but to a limited extent. Out of the seven consumption categories, only gambling is negatively and significantly related to reduced offer-to-requested loan ratio. On the other hand, higher cash usage proxied by ATM withdrawals significantly lowers the lender's willingness to satisfy loan requests, so does repeated borrowing. Further, we find that the lender prefers mature borrowers who are married, having dependents or aged over 30, but dislikes them when they more often are involved in gambling, use cash or request loans repeatedly.

The rest of the paper proceeds as follows. Section 2 discusses the sample and variable construction. Section 3 discusses the empirical design and results. Section 4 concludes. Appendix A reviews the literature and develops our hypotheses, followed by additional empirical results.

2. Sample and variable construction

2.1. Data

Our original dataset contains 153,883 approved loan applications between April 2017 and August 2018. For privacy concerns, the dataset is de-identified and transactions are aggregated to categories. We remove applications with missing loan or borrower characteristics, including bank statement information, e.g., account balance. A few exceptional cases with offered amount larger than requested are also excluded. Our final sample consists of 70,140 loan applications.

2.2. Key variables

2.2.1. Consumer behaviour

Our dataset contains categorized consumption data based on the transaction notes and venues. Specifically, there are seven consumption categories, including gambling, grocery, utility, transportation, insurance, TV subscription and telecommunication expenses, which we normalize by applicants' monthly total spending. In addition to consumption patterns, we also examine applicants' payment methods. Given that cash usage cannot be traced in the dataset, we use ATM withdrawals as a proxy for cash usage. Although ATM withdrawals is not equivalent to cash spending, prior literature has shown a strong correlation between cash on hand and the use of cash as a payment instrument (e.g., Bagnall et al., 2016). We similarly normalize ATM withdrawals by monthly total spending.

2.2.2. Offer-to-requested loan ratio

We focus on the ratio of the lender's offered loan amount to applicant's requested amount as a measure for lending outcome. While loan approval, interest rate and loan processing time are amongst the most common lending outcomes measures in extant studies (e.g., Behr et al., 2011; Ghosh et al., 2021), our dataset contains only approved loans but features the loan amount demanded and supplied, which represents an equilibrium outcome. Such an offer-to-requested ratio ranges from 0 to 1 with a higher value indicating a higher propensity of the lender fully satisfying the demand of the borrower.

2.3. Sample and summary statistics

For loan characteristics, our sample further includes requested loan maturity, loan purpose, and a repeated loan indicator. We have

Table 1
Summary statistics.

Variable	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Panel A: Lending decision variables					
Offered amount (A$)	3791.09	2138.98	2500	3000	4000
Offer to request	0.73	0.29	0.48	0.81	1.00
Panel B: Cash withdrawals and consumption behaviour data Monthly spending amount (A$):					
Total spend	2806.54	2051.54	1464.78	2344.85	3554.06
ATM	520.34	724.75	93.64	274.43	657.34
Gambling	83.83	402.91	0.00	0.00	7.97
Utility	66.80	125.82	0.00	0.00	93.03
Grocery	236.92	256.26	57.92	154.97	324.62
Insurance	72.69	141.70	0.00	0.00	92.86
TV	14.71	36.31	0.00	0.00	12.16
Telecom	141.57	147.94	30.42	105.57	202.78
Transport	24.31	48.16	0.00	2.73	25.31
Monthly spending normalized by total spending (%):					
ATM	19.85	19.92	4.42	13.06	29.76
Gambling	2.17	7.84	0.00	0.00	0.33
Utility	2.16	4.22	0.00	0.00	2.99
Grocery	10.01	10.29	2.70	7.09	13.98
Insurance	2.39	4.69	0.00	0.00	3.20
TV	0.54	1.45	0.00	0.00	0.46
Telecom	6.18	7.09	1.29	4.30	8.59
Transport	1.28	3.10	0.00	0.11	1.11
Panel C: Loan application characteristics					
Requested amount (A$)	6179.27	3782.75	3000	5000	9000
Requested duration (months)	22.64	9.47	12	24	27
Repeat	0.28	0.45	0.00	0.00	1.00
Panel D: Borrower characteristics					
Veda score	545.05	128.16	451	543	636
Age	31	10.31	23	28	37
Salary	3966.51	2942.22	2782	3400	4448
Rent	617.44	1080.18	100	420	900
Loan commit	348.54	842.81	0	200	500
Living expense	550.30	913.89	200	400	650
Married	0.22	0.42	0.00	0.00	0.00
age 30	0.43	0.50	0.00	0.00	1.00
dependant	0.29	0.45	0.00	0.00	1.00

Table 1 provides the descriptive statistics of the sample that contains 70,140 loan applications approved by the lender from April 2017 to August 2018. All dollar amounts of cash withdrawals and categorized expenses are winsorized at the 1st and 99th percentiles by state and time (year-month) before normalization. Detailed variable definitions are provided in Table B1 in the Appendix.

an array of applicant's characteristics, such as credit score (Veda), gender, age, marital status, salary, post code, employment status, home ownership, and having dependents or not, etc. All dollar values are winsorized at the 1st and 99th percentiles by state and year-month before normalization. Appendix Table B1 provides detailed variable definitions.

Table 1 provides the summary statistics. The requested amount mainly falls in the range of $3000 and $9000, whereas the offered amount is mostly between $2500 dollars and $4000. The average offer-to-requested ratio is 73% and the medium 81%. The ATM withdrawal amount accounts about 4.42% to 29.76% of total spending, with a mean of 20% implying a significant role of cash in payment methods for the applicants in our sample.

Table 2 presents the pairwise Pearson correlations. The correlation between offer-to-requested ratio and ATM withdrawal is −0.03, suggesting higher cash usage is negatively associated with the lender's willingness to supply credit and satisfy the demand of the borrower. The correlation between offer-to-requested ratio and all seven categories of consumption is zero or close to zero. Similarly, the correlation between offer-to-requested ratio and repeated borrowing, as well as borrower characteristics, is weak and close to zero. It is, however, significantly and negatively correlated with the requested amount and duration, and positively correlated with borrower's credit score, as expected. The correlation matrix suggests that multicollinearity is not a concern for our analyses. Given that univariate correlations can masque the true relations between the variables, we next turn to multiple regressions to investigate the role of applicant's consumer behaviour in FinTech lending.

Table 2
Pairwise Pearson correlation.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 Offer to request	1																						
2 Offered amount	0.21	1																					
3 ATM	−0.03	−0.04	1																				
4 Gambling	0	−0.03	−0.01	1																			
5 Utility	0	0.05	−0.19	−0.07	1																		
6 Grocery	0	0	−0.14	−0.12	0.08	1																	
7 Insurance	0	0.07	−0.15	−0.06	0.09	0.03	1																
8 TV	0.01	0	−0.08	−0.02	0.09	0.09	0.05	1															
9 Telecom	0	−0.01	−0.12	−0.07	0.08	0.15	0.05	0.07	1														
10 Transport	0	0	−0.04	−0.03	−0.02	0.07	−0.03	0.01	0.16	1													
11 Total spend	−0.04	0.06	−0.09	0.14	0.07	−0.21	0.06	−0.01	−0.22	−0.18	1												
12 Repeat	0.08	−0.13	−0.09	0.01	0	−0.07	0	0.01	−0.02	−0.03	0.09	1											
13 Married	−0.02	0.11	−0.1	−0.04	0.13	0.02	0.12	0.03	−0.05	−0.1	0.25	−0.03	1										
14 Age_30	0.01	0.12	−0.08	−0.03	0.13	−0.03	0.11	0.05	−0.16	−0.19	0.35	0	0.37	1									
15 Age	0.04	0.15	−0.09	−0.04	0.14	−0.05	0.13	0.06	−0.17	−0.2	0.36	0	0.38	0.82	1								
16 dependant	−0.01	0.05	−0.08	−0.05	0.13	0.08	0.04	0.06	−0.06	−0.14	0.2	−0.03	0.39	0.31	0.24	1							
17 Requested amount	−0.66	0.49	−0.02	−0.03	0.04	−0.01	0.06	−0.01	0	0	0.09	−0.14	0.1	0.08	0.08	0.04	1						
18 Requested duration	−0.46	0.29	−0.03	−0.04	0.04	0.05	0.02	0.02	0.01	−0.06	0.01	−0.1	0.06	0.06	0.05	0.06	0.6	1					
19 Vedascore	0.28	0.49	−0.01	−0.01	0.05	0.04	0.07	0	−0.02	0.02	0.05	−0.08	0.11	0.14	0.2	0.05	0.13	0.02	1				
20 Salary	−0.03	0.1	−0.05	0.02	0.03	−0.1	0.05	0	−0.1	−0.06	0.34	0.04	0.11	0.19	0.2	0.06	0.11	−0.02	0.06	1			
21 Rent	0.01	0.06	−0.17	−0.04	0.04	−0.11	0	−0.02	−0.12	−0.07	0.35	−0.01	0.11	0.18	0.19	0.12	0.04	0	0.08	0.23	1		
22 Loan commit	−0.03	0.01	−0.11	−0.01	0	−0.09	0.03	−0.01	−0.08	−0.08	0.29	0.03	0.07	0.13	0.15	0.05	0.04	0.03	−0.02	0.15	0.1	1	
23 Living exp	0.01	0.07	−0.1	−0.01	0.03	−0.05	0.02	−0.01	−0.07	−0.05	0.27	−0.01	0.1	0.14	0.15	0.09	0.04	−0.01	0.08	0.19	0.29	0.11	1

Table 2 provides the pairwise Pearson correlations of key variables. Detailed variable definitions are provided in Table B1 in the Appendix.

Table 3
Consumer behaviour and offer-to-requested loan ratio.

Dependant variable: offer-to-requested ratio	(1)	(2)	(3)	(4)
Repeat	−0.011***	−0.011***	−0.011***	−0.011***
	(−4.08)	(−4.06)	(−3.83)	(−4.30)
ATM	−0.020**	−0.020***	−0.019**	−0.016*
	(−2.92)	(−2.94)	(−2.74)	(−2.03)
Gambling	−0.022**	−0.022**	−0.023**	−0.022**
	(−2.18)	(−2.23)	(−2.29)	(−2.14)
Utility	−0.001	0.002	−0.002	0.007
	(−0.09)	(0.14)	(−0.19)	(0.43)
Grocery	−0.003	−0.003	−0.002	−0.003
	(−0.23)	(−0.27)	(−0.21)	(−0.28)
Insurance	0.022	0.023	0.026*	0.030**
	(1.56)	(1.66)	(2.01)	(2.41)
TV	0.053	0.052	0.038	0.028
	(1.62)	(1.63)	(1.20)	(0.58)
Telecom	−0.000	−0.001	−0.002	0.007
	(−0.02)	(−0.08)	(−0.16)	(0.42)
Transport	−0.048	−0.046	−0.060*	−0.065*
	(−1.39)	(−1.31)	(−1.84)	(−1.89)
Controls & Baseline Fixed Effects	Full	Full	Full	Full
State Fixed Effects	Yes			
Time (Year-Month) Fixed Effects	Yes	Yes	Yes	
State × Time Fixed Effects				
Post code Fixed Effects			Yes	Yes
Post code × Time Fixed Effects				
Observations	70,140	70,136	69,950	63,925
Adjusted R^2	0.686	0.687	0.689	0.700

Table 3 reports the OLS estimation results of the baseline model (Eq. (1)). For simplicity, we report only the coefficient estimates of repeated borrowing, ATM withdrawal, and the seven consumption categories. In all specifications, we control for all available loan and borrower characteristic variables. Table B2 in the Appendix provides the full results. Numbers in parentheses are standard errors clustered at the applicant and time (year-month) level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table B1 in the Appendix.

3. Empirical design and results

3.1. Baseline regression

We investigate the relationship between applicant's consumer behaviour and credit supply using the following loan-level regression specification:

$$\text{Offer} - \text{to} - \text{request} = \beta_0 + \beta_1\, Repeat + \beta_2\, ATM + \lambda C + \gamma X + \text{Fixed Effects} + \varepsilon \tag{1}$$

where C is a vector of the consumption variables, including the categorized expenses for gambling, grocery, utility, transportation, insurance, TV subscription and telecommunication. *Repeat* is an indicator for whether the loan is requested by a new applicant or existing ones. X is a vector of the control variables including the loan and borrower characteristics. Heteroskedasticity-robust standard errors are double clustered by applicant and year-month.

Table 3 reports the OLS estimation results of our baseline model (Eq. (1)). We find that, across all specifications, repeated borrowing is associated with a lower offer-to- requested ratio, significant at the 1% level, after controlling for a wide range of loan and borrower characteristics. Compared to first-time borrowing, repeated borrowing on average has an offer-to-requested ratio that is lower by 0.011, or about 3.79% of the sample standard deviation of 0.29. A higher cash usage proxied by ATM withdrawal is similarly negatively related to the offer-to-requested ratio, statistically significant at the 10% level at least. Specifically, a one-standard-deviation increase in ATM withdrawal is associated with a 0.004 reduction in the offer-to-requested ratio, which is about 1.37% of the sample standard deviation of 0.29.[1] Given a mean requested amount of A$6179, this is about A$25 less offered. This amount seems small, but in fact is larger than the average monthly transport spending of A$24 for the loan applicants in the sample. amongst the seven consumption categories, gambling expenses exhibit a negative association with offer-to-requested ratio, statistically significant at the 5% level across all model specifications. A one-standard-deviation increase in gambling expenses is associated with a 0.002 reduction in offer-to-requested ratio, which is about 0.59% of the sample standard deviation. In the most conserve specification, column (4), where we include post code – time fixed effects to capture time-varying local characteristics, we also document a positive

[1] Given an estimated coefficient of ATM withdrawal of −0.02 and a sample standard deviation of 0.1992, a one-standard-deviation increase translates to about 0.02*0.1992=0.00398.

Table 4
Heterogeneous effects of gambling and cash usage on offer-to-requested loan ratio for mature applicants.

Dependant variable: offer-to-requested ratio	(1)	(2)	(3)	(4)
Panel A: Married				
ATM	−0.014**	−0.015**	−0.013*	−0.009
	(−2.18)	(−2.19)	(−1.97)	(−1.09)
Gambling	−0.021*	−0.021*	−0.023*	−0.026**
	(−1.88)	(−1.92)	(−2.05)	(−2.17)
Married	0.009***	0.009***	0.009***	0.008**
	(4.00)	(4.07)	(3.55)	(2.43)
ATM × Married	−0.030**	−0.031**	−0.031**	−0.040**
	(−2.69)	(−2.86)	(−2.71)	(−2.89)
Gambling × Married	0.000	−0.001	0.007	0.036
	(0.01)	(−0.04)	(0.24)	(1.29)
Panel B: Have dependents				
ATM	−0.016**	−0.016**	−0.014**	−0.011
	(−2.34)	(−2.40)	(−2.14)	(−1.41)
Gambling	−0.017	−0.018	−0.018	−0.020*
	(−1.48)	(−1.54)	(−1.52)	(−1.75)
dependant	0.002	0.002	0.003	0.006*
	(0.85)	(0.80)	(1.20)	(1.76)
ATM × dependant	−0.017*	−0.016*	−0.018**	−0.022**
	(−1.92)	(−1.87)	(−2.29)	(−2.44)
Gambling × dependant	−0.021	−0.019	−0.025	−0.007
	(−1.03)	(−0.95)	(−1.23)	(−0.30)
	(−4.08)	(−4.07)	(−3.83)	(−4.29)
Panel C: Over 30 years old				
ATM	−0.013	−0.013	−0.011	−0.008
	(−1.65)	(−1.66)	(−1.45)	(−0.85)
Gambling	−0.015	−0.015	−0.018	−0.025*
	(−1.11)	(−1.18)	(−1.38)	(−1.89)
Age 30	0.005**	0.005**	0.006***	0.006***
	(2.87)	(2.88)	(3.32)	(2.94)
ATM × Age 30	−0.018**	−0.018**	−0.018**	−0.020**
	(−2.81)	(−2.92)	(−2.87)	(−2.33)
Gambling × Age 30	−0.022	−0.020	−0.015	0.009
	(−1.01)	(−0.96)	(−0.72)	(0.42)
Controls & Baseline Fixed Effects	Full	Full	Full	Full
State Fixed Effects	Yes			
Time (year-month) Fixed Effects	Yes		Yes	
State × Time Fixed Effects		yes		
Post code Fixed Effects			Yes	
Post code × Time Fixed Effects				Yes
Observations	70,140	70,136	69,950	63,925

Table 4 examines the heterogeneous effects of gambling and cash usage on offer-to-requested loan ratio for mature applicants. For simplicity, we report only the coefficient estimates of ATM withdrawal, gambling expenses, and the proxies for mature applicants, as well as their interactions. In all specifications, we control for all available loan and borrower characteristic variables. Numbers in parentheses are standard errors clustered at the applicant and time (year-month) level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table B1 in the Appendix.

impact of insurance expenses and a negative impact of transportation expenses on the offer-to-requested ratio, statistically significant at the 5% and 10% respectively. These findings support Hypotheses H1a, H2a and H3a.

3.2. Robustness

Following Behr et al. (2011), we construct two alternative proxies of lending relationship. The first is an integer variable denoting the number of loan applications lodged before, and the second a category variable indicating the ordinal number of the loan application from an applicant. Appendix Table B3 shows the results using the alternative proxies and confirms that our results remain qualitatively unchanged. Further, in untabulated results, we repeat all our baseline estimations using the sample excluding loan applications from borrowers who have defaults previously and find that our results are qualitatively the same.

3.3. Further results

Next, we focus on gambling behaviour, cash usage and repeated borrowing and their effects on lender's credit supply conditional on the applicant's demographics, especially the "maturity" status. Specifically, in the baseline model, we further interact proxies for

Table 5
Heterogeneous effects of repeated borrowing on offer-to-requested loan ratio for mature applicants.

Dependant variable: offer-to-requested ratio	(1)	(2)	(3)	(4)
Panel A: Married group				
Repeat	−0.009***	−0.009***	−0.009***	−0.009***
	(−3.53)	(−3.53)	(−3.18)	(−3.79)
Married	0.006***	0.006***	0.006**	0.003
	(3.13)	(3.17)	(2.53)	(1.23)
Repeat × Married	−0.009**	−0.009**	−0.008*	−0.008
	(−2.26)	(−2.21)	(−1.99)	(−1.49)
Panel B: Group with dependents				
Repeat	−0.008**	−0.008**	−0.007**	−0.007**
	(−2.79)	(−2.79)	(−2.56)	(−2.68)
dependant	0.002	0.002	0.003	0.005
Repeat × dependant	(0.66)	(0.70)	(0.83)	(1.50)
	−0.013***	−0.013***	−0.012***	−0.014***
	(−3.53)	(−3.57)	(−3.43)	(−3.38)
Panel C: Group over 30 years old				
Repeat	−0.005	−0.005	−0.005	−0.006**
	(−1.57)	(−1.61)	(−1.58)	(−2.35)
Age 30	0.005***	0.005***	0.005***	0.005***
Repeat × Age 30	(4.11)	(4.06)	(4.38)	(3.27)
	−0.015***	−0.015***	−0.014***	−0.011***
	(−4.98)	(−5.11)	(−4.81)	(−3.70)
Controls & Baseline Fixed Effects	Full	Full	Full	Full
State Fixed Effects	Yes			
Time (year-month) Fixed Effects State × Time Fixed Effects	Yes	Yes	Yes	
Post code Fixed Effects			Yes	
Post code × Time Fix Effects				Yes
Observations	70,140	70,136	69,950	63,925

Table 5 examines the heterogeneous effects of repeated borrowing on offer-to-requested loan ratio for mature applicants. For simplicity, we report only the coefficient estimates of repeated borrowing and the proxies for mature applicants, as well as their interactions. In all specifications, we control for all available loan and borrower characteristic variables. Numbers in parentheses are standard errors clustered at the applicant and time (year-month) level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table B1 in the Appendix.

applicant's maturity and each of the three measures: gambling spending, ATM withdrawal, and the *Repeat* indicator. We consider an applicant as mature if he or she is married, having dependents or aged over 30.

Table 4 shows that, ceteris paribus, lender prefers applicants who are married or aged over 30, given the positive and significant coefficients across all specifications. Having one or more dependents does not disadvantage the applicant. Gambling and cash usage proxied by ATM withdrawal, however, significantly reduce the lender's unconditional willingness to offer as much loan as requested. More importantly, for the mature applicants who are married, having dependents or aged over 30, cash usage increasingly reduces the likelihood of lender satisfying their loan requests. For example, compared to the unmarried applicants, a one-standard-deviation increase in cash usage proxied by ATM withdrawal for married applicants further reduce the offer-to-requested ratio by about 0.006, which is more than twice as large as the unconditional effect. Gambling expense, although not statistically significant, also reveals a negative coefficient, which suggests that gambling may lower the chance of having loan requests approved by the lender.

Table 5 shows a similar effect of repeated borrowing on lender's offer-to-requested loan ratio. Across all specifications, repeated borrowing is negatively associated with lender's willingness to satisfy applicants' loan requests, and such effect is stronger for mature applicants who are married, having dependents or aged over 30. However, being married and aged over 30 are positively and significantly related to offer-to-requested ratio, so does having dependents, which is not statistically significant though.

In short, we find that the lender prefers mature applicants and is more likely to satisfy mature applicants' loan requests. But mature applicants with higher gambling expenses and cash usage, or those repeatedly resort to short-term credit, receive lesser than requested, lending support to Hypotheses H1b, H2b and H3b.

4. Conclusion

This study examines the relationship between consumer behaviour and credit access using a novel data by a leading Australian FinTech lender specialized in short-term consumer credit products. Our findings provide an Australian perspective to the growing literature on FinTech lending which uses primarily U.S. data. Our unique dataset reveals that FinTech lender's lending decisions depend on loan applicants' consumer behaviour. To the best of our knowledge, we are amongst the first to study the effect of consumer behaviour on FinTech lending, while most studies focus on the implications of FinTech lending on borrowers (e.g., Gathergood et al., 2019; Di Maggio and Yao, 2021) or the prediction of defaults (e.g., Khandani et al., 2010).

This study has its limitation. Due to the data constraint, we can only show the association, but not causal relation, between loan applicant's consumer behaviour and FinTech lending. Nevertheless, we believe that the findings on the association between consumer behaviour and FinTech lending may still be of interests to FinTech borrowers, academics, and/or regulators. For example, our findings suggest that in the FinTech era, loan applicants need to be aware that their cash usage and gambling expenses can affect their borrowing capacity.

CRediT authorship contribution statement

Mingze Gao: Conceptualization, Methodology, Writing – review & editing. **Henry Leung:** Supervision, Conceptualization, Writing – review & editing. **Linhui Liu:** Conceptualization, Data curation, Methodology, Formal analysis, Validation, Writing – original draft, Investigation, Writing – review & editing. **Buhui Qiu:** Supervision, Conceptualization, Writing – review & editing.

Data availability

The data that has been used is confidential.

Appendices

Appendix A Hypothesis Development

Soft information

Literature shows that the application of text mining techniques on soft information such as descriptive texts and writing styles in loan applications enhances default rate prediction models (Dorfleitner et al., 2016; Herzenstein et al., 2011; Jiang et al., 2018; Netzer et al., 2019; Wang et al., 2020). Moreover, studies on P2P lending platforms have found that borrowers' social networks tend to play an important role in both lenders' judgements as well as the ex-post performances of loans (Freedman and Jin, 2017; Lin et al., 2013). Similarly, Berg et al. (2020) forecast the default behaviour of customers on a commerce platform where payments are accumulated after products are delivered. They reveal that "digital footprints" such as device type, e-mail providers, and certain other website registration inputs are informative. In comparison to the baseline model that only rely on the credit bureau score, the combined model that incorporates both the digital footprint variables and the credit bureau score presents a much higher discriminating power in terms of detecting transactions on which consumers eventually fail.

Whilst bank account activities are identified as a source of alternative data utilised by FinTech lenders (Jagtiani and Lemieux, 2019), we conjecture that FinTech lenders can also employ credit-related evidence presented in bank statements to improve loan approval outcomes.

Payment behaviour and borrower demographics

Studies on the role of ATM withdrawals and payment behaviour in the credit market largely focus on how lenders follow the consumption and payment behaviours of borrowers after the loan is granted. The purpose is for the lender to keep track record of the utility generated from the loans and also to evaluate whether the loans have been utilised for the required purpose or not. ATM withdrawals provide borrowers the flexibility to utilise their loan funds at their discretion, which is often prohibited in traditional bank loans (Gomber et al., 2018). Hence, FinTech businesses provide borrowers significant discretion over the following use or usefulness of the granted funds. FinTech companies may only monitor their clients' online payment behaviour, leaving a gap for such borrowers who want to use the borrowed funds for gambling or any other reason other than the one specified in the loan application.

Our work is related to another strand of literature examining on the characteristics of intensive cash users and associated cash transactions. While electronic payment methods have essentially supplanted cash payments in this technological age, traditional payment instruments are still widely utilised, and we discover significant disparities in payment preferences across demographic groups. (Bagnall et al., 2016; Delaney et al., 2019; Doyle et al., 2017). Based on a thorough investigation of payment diary survey data across seven countries, including Australia, Bagnall et al. (2016) identify several universal factors that might drive cash payment. In addition to the card acceptance rate at the point-to-sale, the store's industry or the type of purchase also matters in customers' choice of payment methods. In most nations, a larger proportion of cash spending is recorded at supermarkets, pubs, and fast-food restaurants, most likely owing to convenience (Bagnall et al., 2016). In their multivariate setting where marginal effects of potential regressors are estimated, Bagnall et al. (2016) find that an age of 36 years or older, lower income and lower education could predict a stronger preference of cash payment over non-cash payment. Similar findings are also published by two government studies based on evidence specific to Australia: intensive cash users are disproportionately likely to be older, lower-income, and holding a below- average education degree (Delaney et al., 2019; Doyle et al., 2017).

A focus of our study lies in the effect of repeat borrowing on lending outcomes. Ghosh et al. (2021) suggest that lender-borrower relationship intensity increases the trust of lenders in their borrowers, which in turn significantly reduces the borrowing cost associated with the repeat loan applications. However, lenders can also hold up repeated borrowers, charging a higher markup and/or offering smaller loans.

FinTech lenders, compared to traditional banks, have a technological advantage in tracking verifiable payment information based on cashless service providers. Cash payments, on the other hand, are easier to manipulate and harder for FinTech lenders to track the payment type. More mature applicants are also expected to disproportionately form the habit of using cash more frequently. Therefore, we formalise our first hypothesis, as follows:

H1a. Borrowers who use cash more frequently will be adversely affected in loan outcomes.

H1b. The relationship between cash usage and loan outcomes will be more pronounced for more mature loan applicants.

Consumption behaviour

Literature examining the interaction of consumption behaviour and credit access as well as FinTech lending take an ex-post approach by analysing the borrowers' spending behaviours and financial management upon the receipt of the fund. Inferring from increase in indebtedness and changes in the auto loan balance after the loan receipt, Di Maggio and Yao (2021) attribute the underperformance of FinTech loans compared to non-FinTech loans to borrowers' durable consumption after the collection of funds. Specifically, by the year-end, more than 5 percent of FinTech borrowers are found to report a default, which is about 25% beyond the average default rate in the sample. Taking a closer look at the consumption patterns of FinTech borrowers, Di Maggio and Yao (2021) find that the financial health of FinTech borrowers have shown signs of improvement during the early days of securing their loans but borrowers then start to increase their spending in purchasing a car or luxury goods. The finding provides empirical evidence on the economic model developed by Banerjee et al. (2015), who predict that increased access to credit encourage durable consumption and thereby leading to further borrowing in the subsequent periods.

Based on this literature framework, we propose that repeated FinTech borrowers will be adversely affected in their loan outcomes because of the formation of unhealthy spending habits over the long run given the ease of prior access to loans. In addition, Because older customers are likely to be more deeply rooted in unhealthy spending habits formed over their lifetime than younger customers, we expect that the relationship between repeated FinTech borrowers and loan outcomes will be more pronounced for those customers who are more mature.

Therefore, we formalise our second hypothesis, as follows:

H2a. Repeat borrowers will be adversely affected in loan outcomes.

H2b. The relationship between repeat borrowers and loan outcomes will be more pronounced for more mature loan applicants.

Similar undesirable outcomes are also revealed by a large body of literature investigating the consequences of access to credit in the form of payday loans. Based on a merged dataset of payday loan applications and credit bureau files of U.K. consumers, Gathergood et al. (2019) examine the treatment effect of receiving a payday loan on consumers employing the identification strategy of Regression Discontinuity (RD). Payday loans are found to result in rising indebtedness level, higher propensity of exceed bank overdraft limits and defaults (Gathergood et al., 2019). Moreover, there is also evidence suggesting the access to payday loans can encourage borrowers' gambling activities (Baugh 2016). The heterogeneity of spending behaviours in groups of different demographic profiles is also observed. For example, Das and Das (2020) suggest that the generation Z customers and millennials have relatively more awareness and exhibit mature behaviours in spending the loan obtained from the FinTech lending corporations as compared to the baby boomers and generation X customers (Das and Das, 2020). It is also evaluated that people belonging to these generations spent the loans taken from the FinTech lending corporations in a relatively more productive manner, whereas generation X and baby boomers only incur liabilities without generating any productive outcomes (Das and Das, 2020).

Hence, we conjecture that FinTech borrowers face adverse loan outcomes when higher gambling expenses are shown because of evidence supporting the finding that access to payday loans can encourage borrowers' gambling activities. We also expect that the relationship between involvement in gambling and loan outcomes will be more pronounced for more mature customers given their gambling habit formation over time. We formalise our third hypothesis as follows:

H3a. Borrowers who are more involved in gambling will be adversely affected in loan outcomes.

H3b. The relationship between involvement in gambling and loan outcomes will be more pronounced for more mature loan applicants.

Appendix B

Table B1, Table B2, Table B3

Table B1
Variable definition.

Variable	Definition
Lending decision variables	
Offered amount	The offered loan amount.
Offer to request	The ratio of the offered loan amount to the requested loan amount.
Consumer behaviour	
Total spend	Total spending in dollars incurred by the borrower per month, sum of the monthly non-discretionary and discretionary expenses.
ATM	Monthly ATM withdrawals amount divided by the total spending amount.
Gambling	Monthly spending amount on gambling divided by the total spending amount.
Utility	Monthly spending amount on utilities divided by the total spending amount.
Grocery	Monthly spending amount on groceries divided by the total spending amount.
Insurance	Monthly insurance expenses divided by the total spending amount.
TV	Monthly TV subscription fees divided by the total spending amount.
Telecom	Monthly telecommunication expenses divided by the total spending amount.
Transport	Monthly transportation fees divided by the total spending amount.
Loan application characteristics	
Requested amount	The requested amount of the loan.
Requested duration	The requested duration of the loan.
Loan purpose	Reasons for borrowing stated by the borrower. The most frequently mentioned purposes are debt consolidation, maintenance & accessories, purchase, holiday travel & accommodation, rent or rental bond, and tuition fee.
Repeat	An indicator variable that is equal to one if the applicant had requested loan from the lender prior to the current loan application as marked by the lender.
Loan number	The number of loan applications submitted by the borrower from the beginning of sample period till the submission time of the current loan application.
Borrower characteristics	
Veda score	The credit score of borrower, assigned by the credit agency, Equifax.
Age	Age of the borrower in years at the time of the loan application.
Age 30	An indicator variable that equals one if the borrower is over 30 years old.
Married	An indicator variable that equals one if the borrower is married.
male	an indicator variable that equals one if the borrower is male.
dependant	an indicator variable that equals one if the borrower has dependant(s).
Employment sector	The industry sector the borrower works in, including accounting, sales, advertising & marketing, and 24 other industry sectors.
Employment length	An indicator variable that equals one if the borrower has been employed for more than one year.
Employment type	The borrower's employment status, including full time, part time and self-employed.
Home ownership	Home ownership status stated by the borrower, including renting, owning, and living with friends or others.
Salary	Self-reported monthly salary of the borrower.
Rent	Self-reported monthly rent expenses the borrower is obligated to pay.
Loan commit	Self-reported amount of credit under loan commitment contracts.
Living expense	Self-reported monthly living expense the borrower incurs.

Table B2
Full results of baseline model.

Dependant variable: offer-to-requested ratio	(1)	(2)	(3)	(4)
Repeat	−0.011***	−0.011***	−0.011***	−0.011***
	(−4.08)	(−4.06)	(−3.83)	(−4.30)
ATM	−0.020**	−0.020***	−0.019**	−0.016*
	(−2.92)	(−2.94)	(−2.74)	(−2.03)
Gambling	−0.022**	−0.022**	−0.023**	−0.022**
	(−2.18)	(−2.23)	(−2.29)	(−2.14)
Utility	−0.001	0.002	−0.002	0.007
	(−0.09)	(0.14)	(−0.19)	(0.43)
Grocery	−0.003	−0.003	−0.002	−0.003
	(−0.23)	(−0.27)	(−0.21)	(−0.28)
Insurance	0.022	0.023	0.026*	0.030**
	(1.56)	(1.66)	(2.01)	(2.41)
TV	0.053	0.052	0.038	0.028
	(1.62)	(1.63)	(1.20)	(0.58)
Telecom	−0.000	−0.001	−0.002	0.007
	(−0.02)	(−0.08)	(−0.16)	(0.42)
Transport	−0.048	−0.046	−0.060*	−0.065*
	(−1.39)	(−1.31)	(−1.84)	(−1.89)
Total spend	−0.000**	−0.000**	−0.000**	−0.000**
	(−2.32)	(−2.32)	(−2.56)	(−2.37)

(*continued on next page*)

Table B2 (*continued*)

Dependant variable: offer-to-requested ratio	(1)	(2)	(3)	(4)
ln (Requested amount)	−0.364***	−0.364***	−0.364***	−0.366***
	(−39.24)	(−39.31)	(−39.60)	(−38.09)
Requested duration	−0.000	−0.000	−0.000	−0.000
	(−0.18)	(−0.21)	(−0.12)	(−0.51)
Age	0.000***	0.000***	0.000***	0.000***
	(3.12)	(3.21)	(3.70)	(3.55)
Male	−0.000	−0.000	−0.000	−0.001
	(−0.10)	(−0.08)	(−0.09)	(−0.34)
Married	0.004*	0.004*	0.004*	0.001
	(2.04)	(2.06)	(1.79)	(0.56)
dependant	−0.001	−0.001	−0.000	0.002
	(−0.50)	(−0.49)	(−0.17)	(0.52)
Employment length	0.006***	0.006***	0.006***	0.005**
	(3.15)	(3.06)	(3.09)	(2.77)
Veda score	0.001***	0.001***	0.001***	0.001***
	(21.03)	(21.01)	(21.59)	(21.23)
ln(Salary)	0.021***	0.021***	0.021***	0.021***
	(5.09)	(5.08)	(5.00)	(4.65)
ln(Rent)	−0.000	−0.000	−0.000	−0.000
	(−0.22)	(−0.28)	(−0.28)	(−0.51)
ln(Loan commit)	−0.001***	−0.001***	−0.001***	−0.001**
	(−3.30)	(−3.22)	(−3.16)	(−2.80)
ln(Living expense)	0.002**	0.002**	0.002**	0.002**
	(2.65)	(2.58)	(2.21)	(2.60)
Loan Purpose Fixed Effects	Yes	Yes	Yes	Yes
Employment Type Fixed Effects	Yes	Yes	Yes	Yes
Employment sector Fixed Effects	Yes	Yes	Yes	Yes
Home Ownership Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes			
Time (year-month) Fixed Effects	Yes		Yes	
State × Time Fixed Effects		Yes		
Post code Fixed Effects			Yes	
Post code × Time Fixed Effects				Yes
Observations	70,140	70,136	69,950	63,925
Adjusted R^2	0.686	0.687	0.689	0.700

Table B2 reports the full OLS estimation results of the baseline model (Eq. (1)). Numbers in parentheses are standard errors clustered at the applicant and time (year-month) level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table B1 in the Appendix.

Table B3
Repeated borrowing and offer-to-requested loan ratio.

Panel A: Loan number	(1)	(2)	(3)	(4)
Loan number	−0.009***	−0.009***	−0.008***	−0.008***
	(−6.65)	(−6.64)	(−6.44)	(−6.33)
Controls & Baseline Fixed Effects	Full	Full	Full	Full
State Fixed Effects	Yes			
Time (year-month) Fixed Effects	Yes		Yes	
State × Time Fixed Effects		Yes		
Post code Fixed Effects			Yes	
Post code × Time Fixed Effects				Yes
Observations	70,140	70,136	69,950	63,925
Adjusted R^2	0.687	0.687	0.689	0.700
Panel B: Loan number dummies				
2nd loan	−0.008***	−0.008***	−0.008***	−0.006***
	(−4.73)	(−4.69)	(−3.98)	(−3.05)
3rd loan	−0.019***	−0.019***	−0.018***	−0.016***
	(−6.23)	(−6.16)	(−6.03)	(−5.02)
4th loan	−0.026***	−0.025***	−0.024***	−0.021**
	(−4.36)	(−4.32)	(−4.25)	(−2.80)
5th loan or more	−0.045***	−0.045***	−0.042***	−0.044***
	(−5.38)	(−5.32)	(−5.12)	(−4.99)
Controls & Baseline Fixed Effects	Full	Full	Full	Full
State Fixed Effects	Yes			

(continued on next page)

Table B3 (*continued*)

Panel B: Loan number dummies				
Time (year-month) Fixed Effects	Yes		Yes	
State × Time Fixed Effects	Yes			
Post code Fixed Effects		Yes		
Post code × Time Fixed Effects			Yes	
Observations	70,140	70,136	69,950	63,925
Adjusted $R2$	0.687	0.687	0.689	0.700

Table B3 reports the OLS estimation results of the baseline model (Eq. (1)) where we replace the repeated loan indicator with loan number in Panel A and loan number dummies in Panel B. For simplicity, we report only the coefficient estimates of loan number and its dummies. In all specifications, we control for all available loan and borrower characteristic variables. Numbers in parentheses are standard errors clustered at the applicant and time (year-month) level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table B1 in the Appendix.

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