Who uses Fintech products: Evidence from the pay-on-demand market

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Abstract

Pay-on-demand products allow users to obtain access to wages from their upcoming pay in advance. In Australia, providers of pay-on-demand services are able to circumvent regulations around responsible lending by charging a flat 5% 'transaction fee' to users of the platform. Credit risk is assessed through analysis of bank statements, and repayments are directly debited from users' accounts shortly after wages are received. Using transaction-level data obtained from customers at a major Australian financial institution, we examine the frequency of use and repayments from two major pay-on-demand providers. Our findings indicate that users of the platform are typically credit constrained - 90% of users who hold a credit card have exhausted their available balances. Nearly half-of pay-on-demand users incur unpaid payment fees (dishonour fees).

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1 Introduction

To help address consumer problems arising from mismatched pay cycles, pay-on-demand services such as *BeforePay* and *MyPayNow* have recently entered the Australian market. These services enable users to access, for a flat 5% *transaction* fee, a portion of their expected (upcoming) pay cheque before it has been paid into their accounts. Upon the deposit of a user's wage, the amount owed to the pay-on-demand provider is automatically withdrawn from the borrower's linked bank account.

Pay-on-demand products have experienced significant growth as workers have become more interested in receiving their wages at the time of their choosing (Visa, 2019). The rapid development of the products has raised two concerns about the impact of pay-on-demand. First, the underwriting and repayment of pay-on-demand products are largely similar to that of payday loans (e.g., Jeong (2021)), which have been criticised as potentially predatory and welfare destroying (e.g., Melzer (2011); Zinman (2014);Skiba and Tobacman (2019)). Second, pay-on-demand platforms use the same loophole that Buy Now Pay Later (BNPL) platforms have employed to be excluded from the National Consumer Credit Protection (NCCP) Act. Pay-on-demand providers are not regulated as credit providers because they charge 'transaction costs' and not (specifically) interest. This means the pay-on-demand platforms are not required to perform a credit check under the responsible lending guidelines, which limits their interaction with the credit bureau system and withholds private information related to product usage.

The exclusion shifts the responsibility to use the product responsibly to the users, which extant literature shows can be beneficial to some and harmful to others. For users with adequate financial literacy, the limited information sharing may improve credit access by providing cheaper short-term credit or by serving consumers with a damaged credit history (see Balyuk (2023)). For other consumers, pay-on-demand may begin a cycle of problematic debt use that starts small but accumulates over time to a substantial amount (Gerrans et al., 2022). Other lenders, who cannot observe pay-on-demand usage patterns, are exposed to a negative externality due to the increased opacity of credit scores (Liberman, 2016). For example, the use of pay-on-demand may be associated with higher credit risk, as it is illustrative of a consumer who faces liquidity constraints. Moreover, the lack of credit check by the pay-on-demand platforms may itself attract consumers with higher credit risk, due to potential adverse selection problems. Individuals who use pay-on-demand services may not be able to obtain funding from conventional credit sources.

This paper answers three novel empirical research questions related to the use of pay-on-demand by utilising transaction data from a major Australian financial institution. Firstly, we examine the demographics of pay-on-demand users, and particularly where they lie on the credit risk spectrum. Second, we estimate the proportion of pay-on-demand users who use the product successfully, i.e., repay their loan on time. Third, we consider whether the addition of information related to credit risk from a bank's internal credit score help to predict the amount borrowed and repayment success.

We first compare the characteristics of pay-on-demand users to those of an average Australian and an average Buy Now Pay Later user. Pay-on-demand is predominantly accessed by younger and male consumers. Those who earn a lower income, live in poorer socioeconomic areas, and are in financial hardship are more likely to use pay-on-demand, suggesting that the product is more attractive to people who are more likely to face liquidity constraints. In addition, among our sample, only 17.1% of the consumers have a credit card with the financial institution, and users are concentrated in bands of low credit scores. Thus, pay-on-demand users appear to be more likely to face external financing constraints.

Almost half of users have incurred more than the simple "transaction cost" when using pay-on-demand. 53.5% of users incurred at least one unpaid payment fee, which is a cost imposed by the bank for a failed direct debit request when the user holds an insufficient cash balance. Examining the structural differences among users who did and did not incur unpaid payment fees, the former group have a lower savings balance, earn a smaller income, are less likely to have a credit card, and more likely to be in financial hardship. Those who incur unpaid payment fees have lower credit scores, and are more likely to have had prior delinquencies on their credit cards and high utilisation rates.

This research contributes to the vast literature on payday lending. Although researchers have documented several adverse and unintended impacts of using payday loans (Melzer, 2011), there is a gap in the literature for identifying a valid replacement for payday loans (Edmiston, 2011). To this end, we consider the viability of using pay-on-demand as a potential lower-cost replacement for payday loans.

Second, this paper is related to the nascent literature that studies the impact of pay-on-demand. So far, most studies that analyse pay-on-demand are based on the direct-to-business model (see Baker and Kumar (2018) and Murillo et al. (2022)), whereas in Australia most lenders operate based on the direct-to-customer model. This paper is the first study of pay-on-demand in an Australian context. Our findings shed light on the relatively risky nature of pay-on-demand usage.

Third, we build upon theories of screening and signalling. Ever since Stiglitz and Weiss (1981) documented that asymmetric information restricts allocation efficiency in the credit market, lenders have employed a variety of screening devices to reduce such asymmetry. Traditional consumer credit risk assessments are based on credit scoring, in which lenders access information (credit scores) from a credit bureau to aid their underwriting decision. Pay-on-demand providers do not perform a credit check in the same way, instead relying on bank statement analysis to underwrite loans. Through studying the adverse outcomes for both lenders and borrowers in the absence of a credit check, this paper highlights the importance of transparency in evaluating the credit risk posed by users.

The results of the research should also be of interest to credit users and lenders, as we highlight the potential adverse consequences of using pay-on-demand, including the magnitude and frequency of unpaid payment fees. For lenders, the direct debit feature of pay-on-demand leads to prioritised claims on the borrower's liquid funds. This may impose a negative externality on other lenders, who fall down the pecking order. Additionally, by not performing credit checks, pay-on-demand providers retain private information about customers, reducing the transparency of credit bureau data (Liberman, 2016). Lenders can improve their assessment of credit risks by identifying pay-on-demand usage as a potential risk signal.

The remainder of the study will proceed as follows. Section 2 will summarise the institutional background in which pay-on-demand lenders operate and the literature on the theories and empirical findings that may explain the setups and use cases of pay-on-demand. Section 3 outlines the data and the research design employed by this research, from which some preliminary results are given. Section 4 reported the results produced by the research design, and finally, Section 5 will discuss these findings and conclude the research by pointing out future directions for research in the field of pay-on-demand.

2 Background

2.1 Use case and market size

Pay-on-demand services, also called earned wage access or wage advancement services, enable users to withdraw their wages during the pay cycle before the actual time of payment. Upon the deposit of their next pay cheque, the amount owing is automatically withdrawn from the borrower's linked bank account.

The industry has experienced significant growth since August 2020 (see Figure 1). The total value of payments made by customers has increased by a factor of 40 between August 2020 and January 2022, reaching almost $25 million by the end of 2021. On average, around 5,000 new customers signed up for one of the two platforms over the same period.

The rise in the demand for the product corresponds to the casualisation of workforce in Australia. Many households would struggle to obtain funds in the case of an emergency. For example, the Australian Bureau of Statistics (2022b) found that one in six households

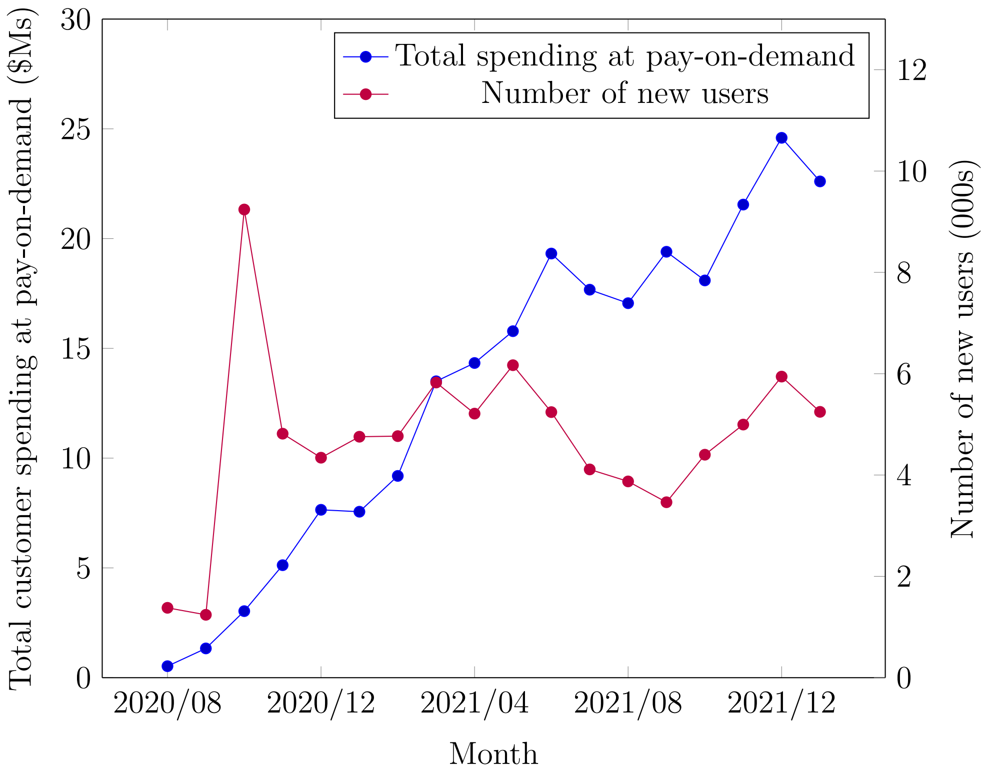

Figure 1: Size and growth of pay-on-demand market

Notes: The graph plots the total consumer spending and the number of new users joining pay-on-demand each month. The two series are obtained from searching through the transaction history of bank's customers from August 2020 to January 2022. If the user has received funds from or made payment to a pay-on-demand provider at any time in the sample, this user will be flagged as pay-on-demand user. We then gather information on the time they first started using pay-on-demand, the amount borrowed from total repayments to pay-on-demand, and the total unpaid payment fees paid by the users.

could not raise \$2,000 within a week, while 5.4% of households would not even be able to come up with \$500. The inability to raise funds may not simply reflect a lack of income, but potentially a mismatch in the timing of cash flows. Casual workers (including freelance or gig workers), as opposed to those with regular salaried employment are especially likely to have lumpy pay cycles, or volatile incomes. In such cases, wages can have been earned, but not yet received.

Those who live 'pay cheque-to-pay cheque' may face financial constraints towards the end of their pay cycle. Prior research (Gelman et al., 2014) has shown that households with limited liquidity spend a large proportion of their funds over the four days following their payday. Moreover, this so-called 'payday effect' often materialises through spending on non-recurring expenses. An inability to retain liquid funds throughout the pay cycle may force households into using expensive, possibly welfare-reducing, external short-term finances when faced with an unexpected liquidity need.

Nearly a quarter of the Australian workforce now are casual workers, who may be earning lumpy or volatile wages due to sickness or changes in shift (Holton, 2022). Such workers experience the strongest payday effect (Gelman et al., 2014), and may realise the greatest benefits from the access to short-term credit.

2.2 Managing credit risks

Pay-on-demand platforms are susceptible to the risk of information asymmetry in the provision of wage advancement, like any other credit providers in the case of Stiglitz and Weiss (1981). To remain outside the regulatory reach of the NCCP Act, pay-on-demand platforms are unable to charge different interest rates (or dollar transaction costs) to different consumers. Thus, platforms typically design their terms of use to screen overly risky borrowers and promote timely repayment of debt (see Table 1 for a summary of key terms and conditions). To use pay-on-demand services, applicants need to submit identification and at least two months of bank account transaction data (for income and expense verification). Consistent with Stiglitz's (1975) theory of screening, pay-on-demand providers employ proprietary screening algorithms to learn more about a borrower's intrinsic creditworthiness. Algorithms at the back end of each platform read the transaction statements and quantify the risk of each borrower. Riskier applicants are consequently denied access to the product.

Criteria	***MyPayNow***	***BeforePay***
Eligible Wage	>$450 per week	>$300 per week
Other Eligibility Criteria	Pass the credit assessment Wage is deposited into the bank account linked to pay-on-demand lenders that can be directly debited Full-time, part-time, casual worker or contractor, or are an on-demand worker Have regular pay schedule (weekly, fortnightly, monthly).	
Maximum Credit	5% transaction cost per advancement	
Loan Amount	$50-$1,200	$50-$1,250

Table 1: Key terms of *MyPayNow* and *BeforePay*

A key feature of pay-on-demand that distinguishes it from traditional credit instruments is that it only charges "transaction" costs, not nominal interest. By not charging interest, neither *BeforePay* nor *MyPayNow* are subjected to the National Consumer Credit Protection Act 2009 (NCCP). The NCCP Act explicitly mandates lenders to apply for a credit license; hence regulators have the direct power to supervise the conduct of these lenders (Gerrans et al., 2022). Neither *BeforePay* nor *MyPayNow* performs a credit enquiry via a bureau, as this may limit access to credit by people without a credit score.

The terms and conditions also incentivise the borrowers to repay their advanced wages, as demonstrating a good history of repayment on a platform will increase the maximum accessible wage on subsequent use. Repeated customers are favourable as past successful repayments signals good credit qualities in the future (Boot and Thakor, 1994). In addition, the platforms will cease further credit access until the outstanding balance is repaid, since the termination of future contingent contracts will also reduce moral hazard (Stiglitz and Weiss, 1983). Platforms only allow borrowers to access a fraction of their historically earned pay cheques (less than 25%), which limits potential overborrowing.

The collection mechanism of pay-on-demand also lowers the risk of strategic default, which refers to an action in which borrowers refuse to repay their obligation despite having sufficient liquidity. Pay-on-demand providers directly deduct money from the users' linked accounts to ensure repayments, which enables providers of pay-on-demand to remain a going concern despite charging a low interest rate (Baker and Kumar, 2018).

Using past transaction history and past pay cheques, pay-on-demand providers can estimate the time and day on which users receive their wages. Thus, platforms can debit from a user's bank account shortly thereafter. Assuming platforms' estimates are accurate, the direct debit will ensure that (1) the default rate will remain low because repayments are automatic and (2) the lenders have the most prioritised claim on the borrower's debt in terms of the pecking order because the repayment of pay-on-demand happens first.

Repeated users thus represent the most valuable group of users, as they borrow more from pay-on-demand and they repay a higher proportion of debt. In Figure 2, we plotted the total amount borrowed by the users of pay-on-demand against the length of time that they have used pay-on-demand. A positive correlation between total borrowings and time since first use of pay-on-demand is observed. Users who have stayed with pay-on-demand the longest contribute the greatest amount of revenue earned by the pay-on-demand lenders. Earlier sign-ups mean the users have a longer time to use pay-on-demand, and given that they use pay-on-demand repeatedly, their larger aggregate borrowing contributes to more transaction costs earned by the industry.

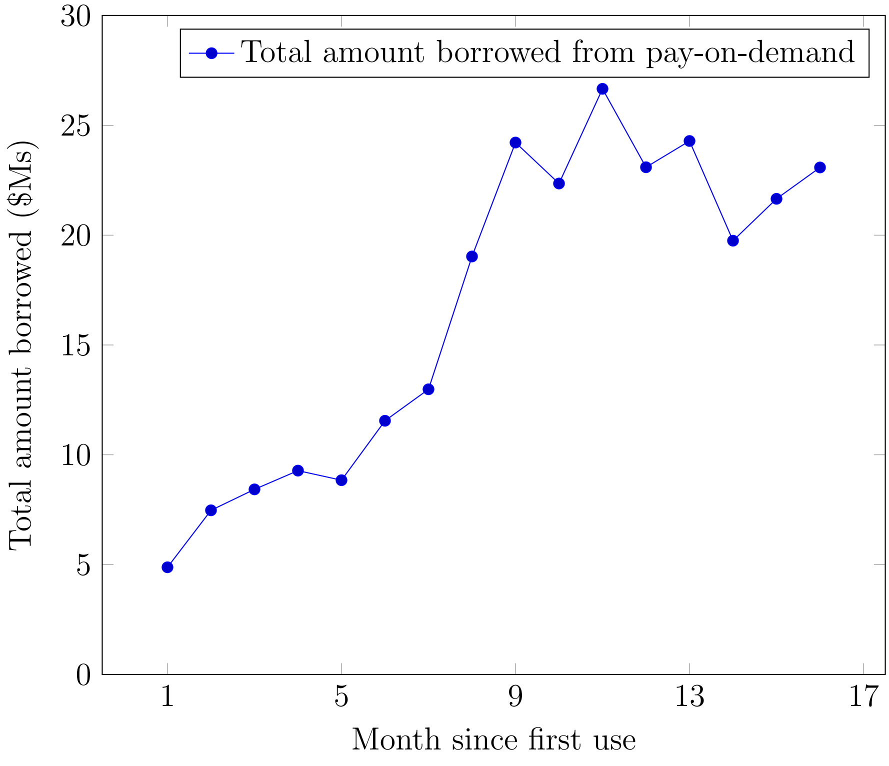

Figure 2: Use of pay-on-demand over time

Notes: This figure plots the total amount that borrowers have borrowed against the duration since the user has started using pay-on-demand. The data source is the same to the one used in Figure 1.

Figure 3 plots the distributions of aggregate frequency and size of repayments to and borrowings from pay-on-demand. Examining the frequency of transactions in Panel A, the vast majority of users access pay-on-demand on multiple occasions. Given the sample period only spans 18 months and more users joined pay-on-demand later in the sample period, it is suggestive that a substantial proportion of users access pay-on-demand regularly. The distribution of number of repayments may not be identical to the number of borrowings, as the users can choose to repay in installments.

Noticeably, the frequency of borrowings and repayments is positively skewed, with more than 15% of the total users using pay-on-demand more than 50 times throughout the sample period. In Panel B, we plot the distribution of the size of borrowings and repayments, and similar patterns can be observed. The median aggregate amount of borrowing for a user is \$2,000, and the total amount repaid is \$1,500. Both the amount borrowed and amount repaid are heavily positively skewed, with more than 30% of the users borrowing and repaying more than \$4,500 throughout the 18-month period.

2.3 Risk to users

The functionality of salary link is also imperative to the borrowers, as a failed direct debit will incur an unpaid payment (dishonour) fee. Borrowers need to ensure there are sufficient funds in their account at the time that the direct debit is made. If an attempt to withdraw funds from the borrower's account is unsuccessful, dishonour fees may be charged by the customer's bank. For example, a \$5 unpaid payment fee, resulting from each failed attempt at direct debit by a pay-on-demand provider, can quickly compound the cost of using the service. [1] Thus, it is imperative to both pay-on-demand platforms (to minimise defaults) and borrowers (to minimise interest charges) to ensure that the customer's pay cycle is estimated accurately. The aim is to ensure that the pay-on-demand platform takes payment shortly after the pay cheque arrives in the borrower's bank account. If the platform attempts to debit the funds too early, they face the risk that the customer has not yet received their wages, and is unable to make payment. However, if an attempt occurs too late, the platform runs the risk that the customer has already spent their wage (or transferred the funds elsewhere).

Unpaid payment fees represent a significant hidden cost to access pay-on-demand. As more and more bank customers start using pay-on-demand, they start paying unpaid payment fees more frequently. In Figure 4, we plot the time series of monthly customer spending on pay-on-demand and total unpaid payment fees paid by the users of pay-on-demand together. The two time series are highly positively correlated. In the early sample periods, when the majority of the sample has not yet become users of pay-on-demand, aggregate spending on pay-on-demand and total unpaid payment fees paid are low. Over time, as more proportion of the sample started using pay-on-demand, more

[1] A typical pay-on-demand loan with an interest rate of 5% over a period of two weeks would imply an equivalent annual rate of around 255%. The same loan with a rate of 10% per fortnight (equivalent to one failed direct debit per cycle), yields an EAR of 1092%.

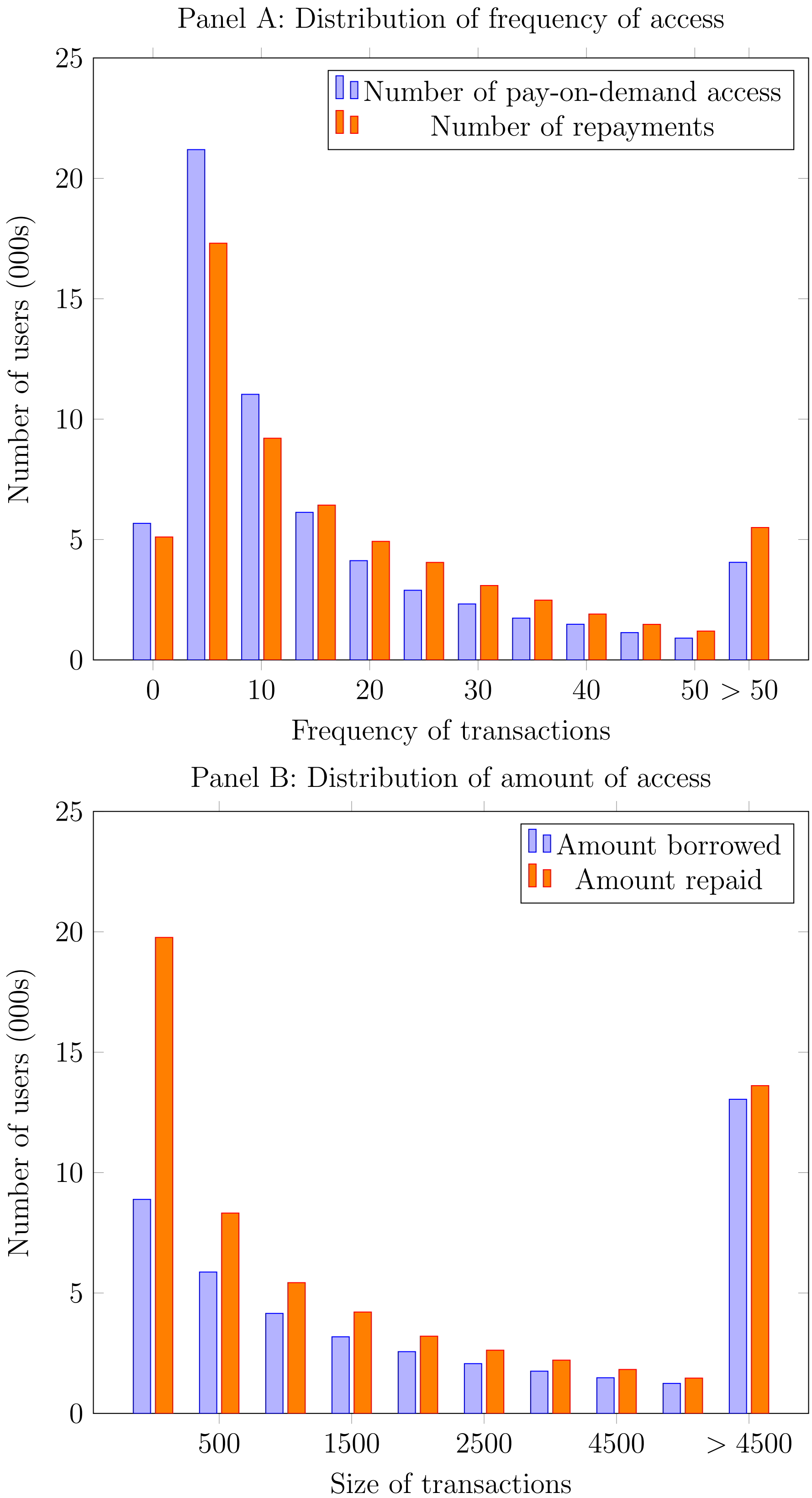

Figure 3: Key user characteristics of pay-on-demand

Notes: This figure presents information on how pay-on-demand is being used by the users. Panel A plots the distribution of frequency of transactions, and Panel B plots the distribution of size of transactions. Frequency and amount of repayment excludes transaction reversals.

unpaid payment fees are paid by these users.

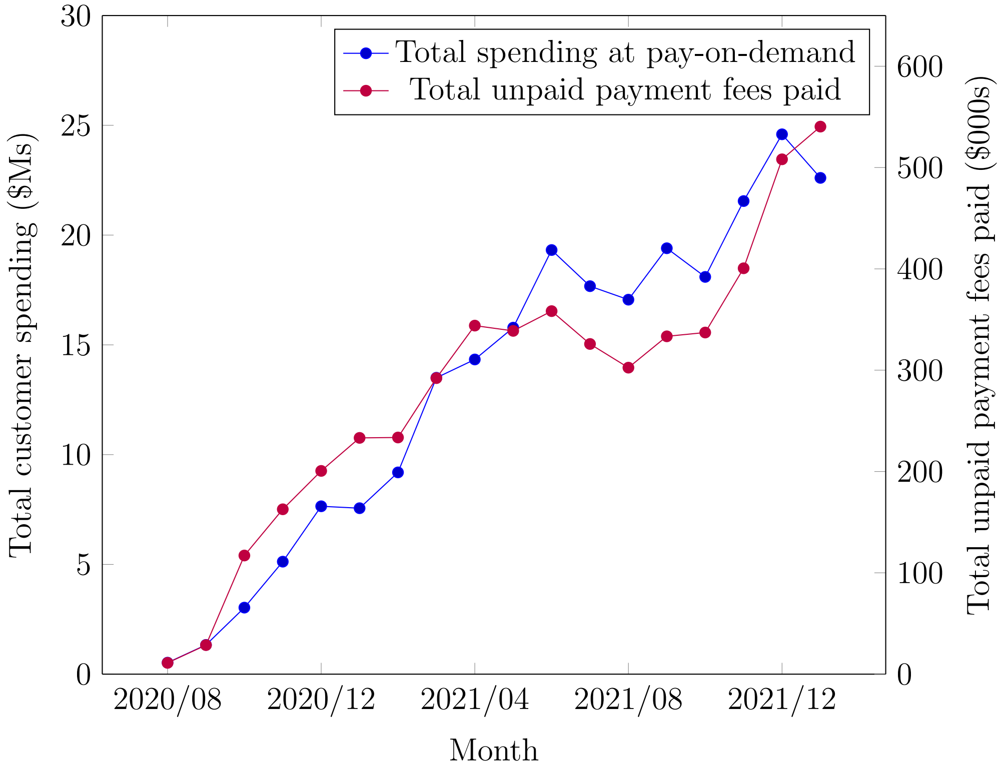

Figure 4: Customer spending and unpaid payment fees

Notes: This figure plots the total customer spending on pay-on-demand and the total unpaid payment fees that users of pay-on-demand paid in each month. Total spending excludes the payments to pay-on-demand that are subsequently reversed. The data source is the same to the one used in Figure 1.

3 Data

3.1 Data source and identification of pay-on-demand users

We explore the transaction data of the debit account of pay-on-demand users in the month of 2022 March, supplied by a major Australian bank. In the data, every transaction is accompanied by a transaction-type code and a description. The users are identified by looking up the transaction details field, and the bank customers are flagged as pay-on-demand users if the field contains keywords like `%BeforePay` or `%MyPayNow`. We take note of whether the transaction is a loan or repayment, the transaction amount, the date, and the other party of the transaction.

For each customer, we then obtained two sets of data. The transaction data is first matched with customer-level demographic information, using both unique account-level identifiers and customer-level identifiers. The data set contains information on customer demographics, including age, gender, marital status, salary type, estimated income, benefits or hardship, and socioeconomic decile. Other account holdings (flagging if a customer has a home loan, personal loan, credit card or overdraft facility with the bank) are also recorded in the database. The second data set is obtained from the bank's customer credit card facilities, which includes information related to the credit card balance and limit, utilisation rate, customer risk band/score, and previous delinquency records.

In cleaning the data, the following filters are imposed. Users who are over the age of 65 and under the age of 18 are excluded from the data. Accounts without a gender and whose salary type cannot be identified are excluded to remove the impact of non-retail business pay-on-demand accounts. We also exclude customers whose postcodes cannot be matched to the ABS "Socioeconomic Index for Areas" database, as these users' addresses are PO boxes rather than residential. This yields a final cross-sectional data of 49,866 users, which we then use to perform our analysis.

3.2 Demographic and socioeconomic characteristics

Table 2 reports the summary statistics of the key user characteristics, aiming to answer the question of who uses pay-on-demand. Nearly 3 in 5 pay-on-demand users are male (59.7%), and the median user is 29 years of age. Noticeably, although the eligibility criteria requires users to have a stable income, not all users of pay-on-demand appear to meet this standard. Specifically, 31.1% of the users never received a salary in their linked account, and 9.1% of users' salaries ceased but continued to use the product.

Furthermore, the median income for pay-on-demand users is considerably lower than that of the median Australian, standing at only $31,000. Figure 6 shows that the median income, even after excluding the users with less than $20,000 of annual income, is still considerably than the national average of $62,868 per year (Australian Bureau of Statistics, 2022a). Users with a lower income tends to borrow more, as evidenced by the average loan to income ratio.

We plot the demographic and socioeconomic characteristics of pay-on-demand users in Figure 5. Panel A highlights the frequent use by younger, particularly male individuals. This pattern is consistent with users of other Fintech lending products, such as BNPL (Berg et al., 2021; Australian Securities and Investment Commission, 2020), possibly due to technological preferences and the likelihood of less stable salaries in lower age groups.

Panel B of Figure 5 shows a comparison between pay-on-demand users and the average population, in terms of the socioeconomic decile of their addresses. A higher socioeconomic decile refers to a more affluent residential postcode under the ABS SEIFA classification. Scaling by population density, as seen from the line in Panel B of Figure 5, we see that, on average, people from lower socioeconomic deciles are more likely to

Variable	Mean	Std. Dev	25th Pctl.	Median	75th Pctl
Age	30.93	9.3	24	29	36
Gender (Percent Female)	0.403	0.491	0	0	1
Socioeconomic Decile	5.203	2.892	3	5	8
Income	28.14	27.16	0	31.22	47.49
Always Salary	0.477	0.499	0	0	1
Salary Switching	0.116	0.321	0	0	0
Never Salary	0.311	0.463	0	0	1
Salary Ceased	0.091	0.288	0	0	0
Deposit Savings Balance	845.91	6651.61	94	293	576
Savings > 1000	0.112	0.315	0	0	0
Hardship Flag	0.140	0.345	0	0	0
Benefits Flag	0.044	0.205	0	0	0
Credit Card Flag	0.171	0.377	0	0	0
Personal Loan Flag	0.146	0.353	0	0	1
Utilisation Rate	0.155	0.372	0	0	0
Highly Utilised	0.125	0.33	0	0	0
Credit Card Delinquency Bucket 1+	0.124	0.329	0	0	0
Credit Card Delinquency Bucket 2+	0.054	0.227	0	0	0
Behavioural Score	544.12	243.05	397	559	681
Risk Grade 0	0.074	0.262	0	0	0
Risk Grade 1	0.104	0.306	0	0	0
Risk Grade 2	0.155	0.362	0	0	0
Risk Grade 3	0.210	0.407	0	0	0
Risk Grade 4	0.211	0.408	0	0	0
Risk Grade 5	0.244	0.43	0	0	0
Num. Transactions	2.702	1.792	1	2	4
Num. Unpaid Payment Fees	2.24	4.11	0	0	3
Net Trans Payments	2.09	1.69	1	2	3
Net Trans Loans	1.22	1.43	0	1	2
Net Trans Sum Payments	359.06	256.07	157.5	304.5	525
Net Trans Sum Loans	-250.73	288.18	-400	-150	0

Table 2: Summary statistics of key variables

Notes: This table presents the summary statistics of the key variables that are used in subsequent analysis. The definition of the variables are in Table 6. Savings and product use information are denoted in Australian dollars, income is denoted in thousand Australian dollars. The mean is calculated on the customer level.

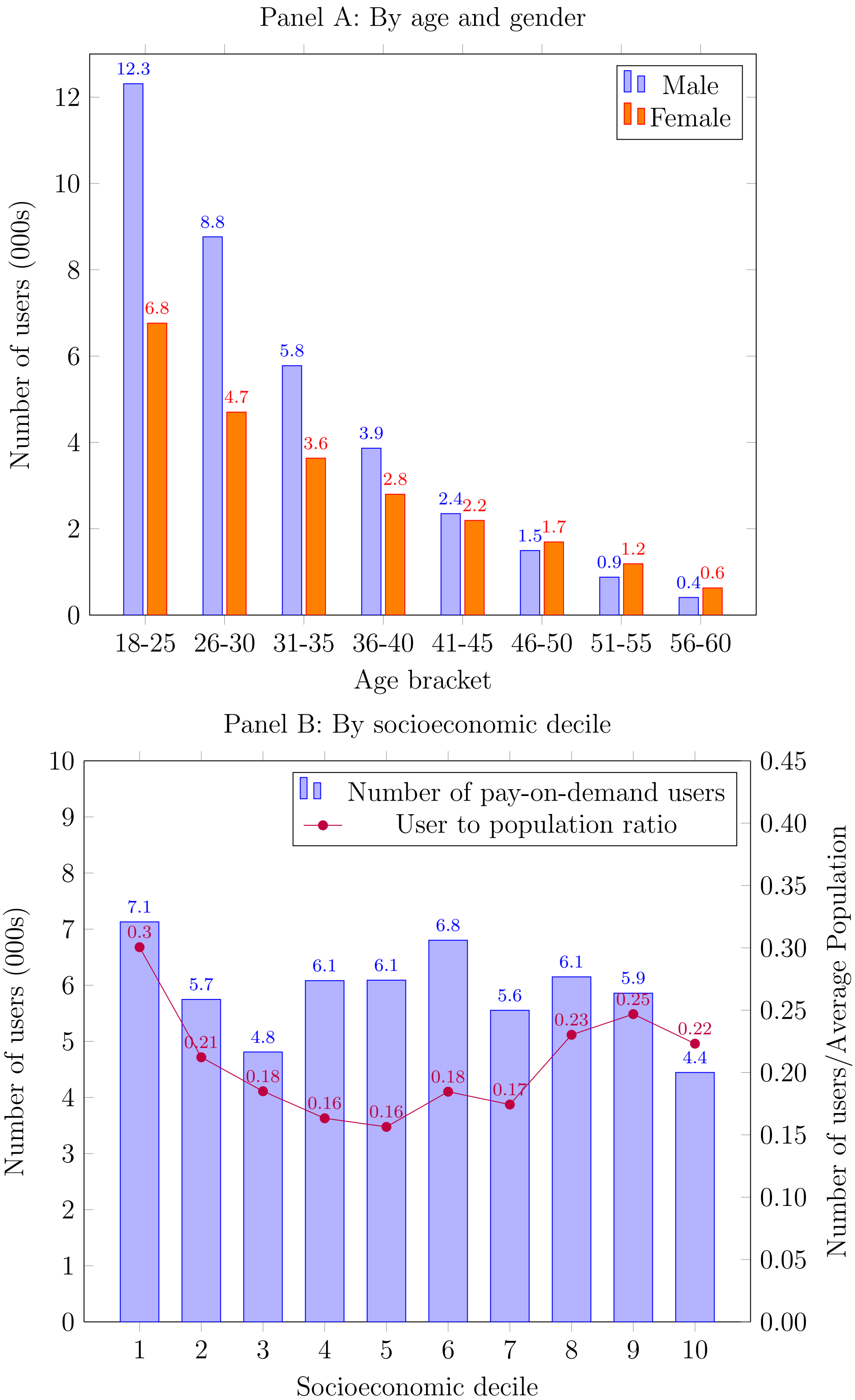

Figure 5: Demographic and socioeconomic characteristics

Notes: This figure plots the distribution of pay-on-demand users in terms of their demographic and socioeconomic information, using the cross-sectional data described in Section 2.3. Panel A plots the number of users in each gender-age group. Panel B presents the number of users in each socioeconomic decile.

use pay-on-demand. For example, we find that 7,100 users of pay-on-demand reside in decile 1 postcodes, which represents about 3 users per 1,000 population in these regions. In contrast, 4,400 users reside in decile 10, which is only 2.2 users per 1,000 population.

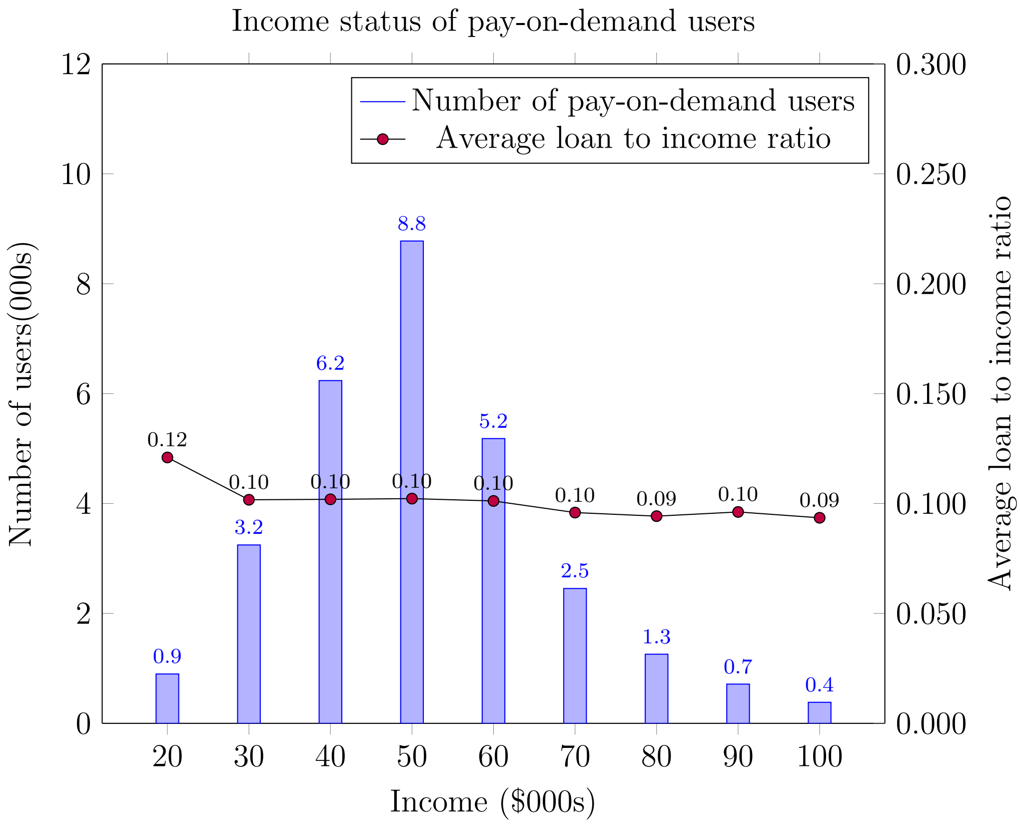

Figure 6: Employment and income status

Notes: This figure plots the distribution of pay-on-demand users in terms of their total earnings, and how heavily they rely on pay-on-demand measured by the average loan-to-income ratio.

3.2.1 Other product co-holdings

The proportion of pay-on-demand users holding a credit card is substantially lower than that of the overall Australian population and users of BNPL services. Specifically, while 17.1% of pay-on-demand users have a credit card, Cooke (2022) find that 13.7 million credit cards are in use among the total Australian population of 25.69 million, and Boshoff et al. (2022) estimate that 30.5% of BNPL users hold a credit card. This discrepancy is attributed to two factors. First, as pay-on-demand does not require a credit check, it has drawn users who are unable to secure credit elsewhere due to poor credit ratings. Second, the service caters primarily to younger users, who are less inclined to use credit cards due to risk aversion and suboptimal credit histories (Lowrey, 2013). On the other hand, 12.5% of pay-on-demand users hold highly utilised credit cards (utilisation rate > 95%), which is significantly higher than the 38%-43% of BNPL users who use over 90% of their credit line on their credit card, according to (Australian Securities and Investment Commission, 2020).

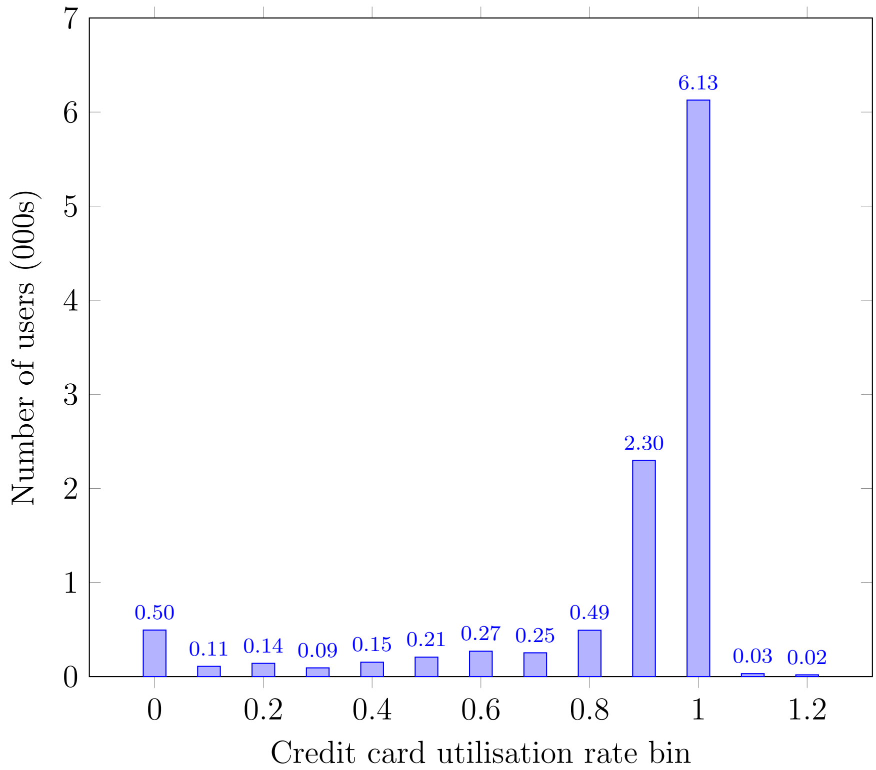

Figure 7: Credit card utilisation

Notes: This figure plots the distribution of credit card utilisation rate among users of pay-on-demand who have a credit card.

Examining the credit card reliance, Figure 7 shows that pay-on-demand users who have a credit card are either near the limit or already over the limit, as the majority of customers have a credit card utilisation rate of over 90%. This could be a sign of financial stress, and a weak signal of defaulting on credit card debt.

Apart from having a higher utilisation rate, pay-on-demand users with credit cards are more likely to have a past delinquency record compared to average credit card users. From Table 2, 12.4% of the total sample had missed at least one credit card payment in the previous 12 months (Credit Card Delinquency Bucket 1+). Given that only 17.1% of users hold a credit card, this indicates that around 70% of credit card users in the pay-on-demand sample have exhibited repayment difficulties on their card.[2] In addition, 5.4%

[2]The 70% figure is approximately the ratio of the 12.4/17.1 per cent of users - it does not include customers who held a card at a previous stage, but not during our sample period.

of our sample have been in Credit Card Delinquency Bucket 2+, indicative of a credit card repayment more than 30 days overdue, representing serious payment difficulties. In contrast, in the sample of BNPL users with credit cards examined by Boshoff et al. (2022), only 23.28% of the credit card users had missed any repayments. Thus, the credit card users with pay-on-demand appear to be relatively high risk customers for the bank.

3.2.2 Credit risk variables

We examine the credit risk in terms of customer risk grades, which is a benchmark that the bank has produced to evaluate the risks of their own customers. A higher risk grade (1 – 4) means the customer more likely to miss repayments. Risk grade 0 is assigned to ungraded customers who recently joined the bank and are unable to be scored. Risk grade 5 is assigned to customers who are difficult to score due to abnormal values of input variables. The relative distribution of risk grades show that bank customers who use pay-on-demand are viewed as higher risk.

Since the majority of pay-on-demand users receive a grade of 3 to 5, they appear to be significantly riskier than the average bank customers, as the median grade is between 2 and 3. In contrast, Boshoff et al. (2022) finds that around 70% of BNPL users fall into risk grades 1 and 2. Anecdotally, users in a risk grade of 3 or higher are unlikely to be approved for a credit card. The high credit risk nature of pay-on-demand users may also imply an inability to to alternative sources of finance. Most of the users with a credit card have already maxed out their credit line. Users without a credit card have have difficulty obtaining one due their relatively high risk grade. Thus, the credit constrained population is a valuable user base to pay-on-demand, providing more incentive for platforms to eschew a credit check. Platform users have the incentive to make repayments in the absence of other sources of accessible funding.

3.3 Pay-on-demand usage pattern

On average, the pay-on-demand platforms attempt to debit a user 2.70 times (*Num. Transactions*). However, out of these repayments, only 2.09 of these are successful (*Net Trans Payments*). Failed repayments consequently lead to the occurrence of unpaid payment fees, amounting to $5 per failed transactions. Further, to minimise the credit loss rate, lenders send multiple direct debit requests to the users' accounts to ensure recollection, so the unpaid payment fees quickly accumulate to a substantial cost of accessing pay-on-demand. Given the average monthly loan size of $250.73, the unpaid payment fee amounts to 4.5% of the total borrowings.

Although pay-on-demand aims to bridge the cash flow timing mismatch between pay-days, in subsequent sections we show that users who experience the strongest earnings volatility tend to use the product the least successfully. Users earning lower wages or inconsistent incomes on are more likely to incur more unpaid payment fees. This imposes more costs on those who use pay-on-demand, which may ultimately limits the extent to which pay-on-demand can improve their financial stability.

3.4 Univariate tests

To better understand the structural differences between successful and unsuccessful pay-on-demand users , we run an unpaired t-test to compare the users in each group. The results of the univariate test are reported in Table 3. Overall, 23,194 of the total 49,866 (46.5% of) users have incurred an unpaid payment fee.

The two groups are of a similar age and gender composition, averaging 31 years and comprising 40% female consumers. Users that have paid an unpaid payment fee are from slightly lower socioeconomic deciles (5.23 vs 5.34).

People that have incurred a dishonour fee tend to be from lower liquidity groups, and are less likely to be in the 'Always Salary' group. On average, people with unpaid payment fees earn \$4,320 less a year and have \$582.73 less savings. People with failed direct debit are also significantly more likely to be in a financial hardship (20.9% vs 7.6%). The lower cash level may contribute to short-term liquidity issues, leading to insufficient balance for direct debit to fail so an unpaid payment fee is incurred.

The credit risk levels measured by the bank's risk grade are correlated with unpaid payment fees. A comparison of the risk grade variables shows that users that have incurred an unpaid payment fee are more likely to be from risk grade 4 and 5, indicating they are riskier or more difficult to score. Other product holdings are similar between the two groups; 17.69% of users with unpaid payment fee and 16.74% of users without unpaid payment fees hold a credit card. Personal loan holdings are similar for those who incur dishonour fees and those who do not. Despite holding similar products, the actual usage patterns in other credit products predicts unsuccessful use of pay-on-demand. Evidence for the said predictability includes failed pay-on-demand users having a higher average credit card utilisation rate and greater rates of prior delinquency on credit cards.

Successful and unsuccessful pay-on-demand users also exhibit different usage patterns in pay-on-demand itself. Consistent with the terms of use, the credit accessible by the users is dynamic, which increases with each successful use (and decreases with each unsuccessful use). Hence, successful users borrow a greater amount of wages (\$229.01 vs \$203.26). The frequency of access is also higher for successful users, as a failed repayment will prevent further withdrawals until the obligation is fulfilled.

The differences between *Num. Transactions Pmt* and *Net Trans Pmt* are indicative of

	Unpaid Payment Fees			No Unpaid Payment Fees				
Variable	N	Mean	Std. Dev	N	Mean	Std. Dev	Difference	P-value
Age	23194	30.82	8.98	26672	30.95	9.53	-0.13	0.1122
Gender (Percent Female)	23194	0.396	0.489	26672	0.406	0.491	-0.01	0.0224
Socioeconomic Decile	23194	5.23	2.83	26672	5.34	2.84	-0.11	<0.0001
Income	23194	25.82	27.14	26672	30.14	27.03	-4.32	<0.0001
Always Salary	23194	0.440	0.50	26672	0.510	0.50	-0.07	<0.0001
Salary Switching	23194	0.113	0.317	26672	0.119	0.324	-0.006	0.035
Never Salary	23194	0.327	0.469	26672	0.299	0.458	0.028	<0.0001
Salary Ceased	23194	0.116	0.3201	26672	0.070	0.256	0.046	<0.0001
Deposit Savings Balance	23194	528.07	4602.77	26672	1110.8	7736.05	-582.73	<0.0001
Savings > 1000	23194	0.0633	0.2436	26672	0.1532	0.360	-0.0899	<0.0001
Hardship Flag	23194	0.209	0.4066	26672	0.076	0.2656	0.133	<0.0001
Benefits Flag	23194	0.0446	0.2065	26672	0.0432	0.2033	0.0014	0.4365
Credit Card Flag	23194	0.1769	0.3816	26672	0.1674	0.3734	0.0095	0.005
Personal Loan Flag	23194	0.1444	0.3515	26672	0.1464	0.3536	-0.002	0.525
Utilisation Rate	23194	0.1685	0.3784	26672	0.1446	0.3676	0.0239	<0.0001
Highly Utilised	23194	0.1422	0.3493	26672	0.1102	0.3131	0.032	<0.0001
Credit Card Delinquency Bucket 1+	23194	0.1476	0.3547	26672	0.1038	0.305	0.0438	<0.0001
Credit Card Delinquency Bucket 2+	23194	0.0714	0.2576	26672	0.0395	0.1948	0.0319	<0.0001
Behavioural Score	23194	442.27	217.22	26672	633.01	229.37	-190.74	<0.0001
Risk Grade 0	23194	0.0716	0.2578	26672	0.0760	0.265	-0.0044	0.049
Risk Grade 1	23194	0.0234	0.1513	26672	0.1754	0.3803	-0.152	<0.0001
Risk Grade 2	23194	0.0858	0.2801	26672	0.2153	0.411	-0.1295	<0.0001
Risk Grade 3	23194	0.2076	0.4056	26672	0.2123	0.409	-0.0047	0.1923
Risk Grade 4	23194	0.2756	0.4468	26672	0.1548	0.3617	0.1208	<0.0001
Risk Grade 5	23194	0.3359	0.4723	26672	0.1660	0.3721	0.1699	<0.0001
Num. Transactions	23194	3.116	1.8117	26672	2.340	1.6986	0.776	<0.0001
Num. Unpaid Payment Fees	23194	4.816	4.9104	26672	0	0	4.816	<0.0001
Net Trans Payments	23194	1.850	1.6677	26672	2.299	1.687	-0.4495	<0.0001
Net Trans Loans	23194	1.101	1.2731	26672	1.318	1.5556	-0.217	<0.0001
Net Trans Sum Payments	23194	222.59	237.74	26672	351.12	261.14	-128.53	<0.0001
Net Trans Sum Loans	23194	-203.26	252.74	26672	-229.01	309.94	25.75	<0.0001

Table 3: Univariate tests of key variables

Notes: This table outputs the unpaired two-sample t-test of users who have incurred an unpaid payment fee and who have not. Savings and product use information are denoted in Australian dollars, income is denoted in thousand Australian dollars. The mean is calculated on the customer level. Variances are unpooled and the Welch modification to the degrees of freedom is applied.

the functionality of the direct debit feature. On average, successful users have a higher *Net Trans Pmt*, but lower *Num. Transactions Pmt*. An average unsuccessful user is charged an unpaid payment fee 4.816 times (equivalently incurring $24.08 in unpaid payment fees) in one month. These charges may be directly related to the missed payment from the platform, or from other failed direct debits (e.g. from other bills).

Evidently, to use the product successfully, users need to have sufficient liquidity on hand, in the form of adequate liquid saving or stable and sufficient income. On the other hand, the prior experience of using credit successfully is also important to reduce unpaid payment fees. Users who avoid unpaid payment fees are more likely to use credit cards successfully, as they have lower utilisation rates and less likely to have previous delinquency. Users who do not pay unpaid payment fees are also less likely to be in financial hardships arrangements.

4 Results

4.1 Who pays unpaid payment fees?

We first examine the determinants of incurring an unpaid payment fee, as it is a signal of an unsuccessful use of pay-on-demand. Both logistic regressions and OLS regressions are used, allowing us to examine the likelihood of incurring unpaid payment fees, and the level of unpaid payment fees, respectively. Table 4 presents the result for the regressions. Columns (1) to (5) of Table 4 report logistic regression outputs, with the dependent variable *Unpaid Payment Fee Flag* taking a value of 1 if the customer paid an unpaid payment fee within the month, and 0 if they did not pay an unpaid payment fee within the month. In Column (6) of Table 4 we estimate an OLS regression, with *Num. Unpaid Payment Fees* being the dependent variable. In Table 4, we increment the number of independent variables, from specification (1), which includes only basic demographic information (*Age*, *Gender*, and *Socioeconomic Decile*) plus information that is readily available from a simple analysis of a customer's bank statement (*Savings>1000*, *Always Salary*, and *CC Flag*). In specifications presented in Columns (2) to (5), we gradually introduce more explanatory variables including income (2), credit card utilisation status (3), other product holdings (4), and credit risk information (5). The OLS model presented in Table 4, Column (6) includes the complete set of independent variables.

The results of the logistic regression models shown in Table 4 indicate little relationship between *Age* and the likelihood of a pay-on-demand user incurring an unpaid payment fee. However, men are significantly more likely than women to pay associated fees when using the product, with significant (negative) coefficients on *Gender* for each of the specified models. Users of pay-on-demand services from a lower *Socioeconomic*

	Unpaid Payment Fee Flag					Num. Unpaid Payment Fees
	Logistics					OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.001	0.001	0.001	0.002*	-0.003***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Gender (Female = 1)	-0.034*	-0.040**	-0.040**	-0.042**	-0.040**	-0.069*
	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.036)
Socioeconomic Decile	-0.010***	-0.010***	-0.009***	-0.007**	-0.005	-0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Savings>1000	-0.975***	-0.975***	-0.955***	-0.894***	-0.683***	-0.837***
	(0.032)	(0.032)	(0.032)	(0.033)	(0.035)	(0.040)
Always Salary	-0.257***	0.089**	0.094**	0.077**	0.079**	0.662***
	(0.019)	(0.037)	(0.037)	(0.038)	(0.040)	(0.103)
Always Salary*log(Income+1)		-0.038***	-0.038***	-0.034***	-0.031***	-0.083***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.010)
CC Flag	0.139***	0.147***	-0.599***	-0.533***	-0.476***	-0.600***
	(0.024)	(0.024)	(0.050)	(0.050)	(0.057)	(0.075)
CC Flag * CC Delinquency Bucket 1+			0.444***	0.107**	-0.225***	-0.625***
			(0.051)	(0.054)	(0.056)	(0.099)
CC Flag * CC Delinquency Bucket 2+			0.525***	0.260***	0.300***	0.482***
			(0.065)	(0.070)	(0.067)	(0.147)
CC Flag * Highly Utilised			0.541***	0.456***	0.273***	0.163*
			(0.057)	(0.055)	(0.059)	(0.091)
Risk Grade 1					-1.861***	-1.298***
					(0.049)	(0.036)
Risk Grade 2					-0.827***	-0.711
					(0.032)	(0.043)
Risk Grade 4					0.615***	1.187***
					(0.028)	(0.056)
Risk Grade 5					0.628***	1.199***
					(0.028)	(0.054)
Personal Loan Flag				-0.012	0.041	0.214***
				(0.027)	(0.028)	(0.052)
Hardship Flag				1.080***	0.595***	1.714***
				(0.030)	(0.033)	(0.083)
Benefit Flag				0.003	0.001	0.074
				(0.045)	(0.047)	(0.083)
Constant	0.095***	0.081**	0.085**	-0.065*	0.177***	2.302***
	(0.037)	(0.037)	(0.037)	(0.038)	(0.043)	(0.073)
N	49,866	49,866	49,866	49,866	49,866	49,866
Pseudo R^2	0.019	0.020	0.027	0.046	0.120	
R^2						0.099
Adjusted R^2						0.098
Residual Std. Error						3.913 (df=49848)
Notes:						***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 4: Predictors for unpaid payment fees

The table reports the regression output of unpaid payment fee on demographic, credit information and other controls. Column(1) to (5) are the results from logistics regression of a dummy variable equal to one if the user has incurred an unpaid payment fee. An OLS regression of the number of unpaid payment fees is reported in column (6). Heteroeskedasticity consistent standard errors of the coefficients are included in the brackets. Pseudo R^2 refers to the McFadden's pseudo R^2.

Decile are more likely to pay unpaid payment fees, in all specifications other than Model (5), which includes the bank's credit Risk Grades. To provide an interpretation of the coefficient of *Socioeconomic Decile*, which takes a value of approximately -0.010 in models (1) to (3), a user living in a postcode assigned to the highest socioeconomic decile (Decile 10) exhibits an odds ratio of $\exp(-0.010 \times 9) = 0.914$. Thus, a user in Decile 10 is approximately 9.14% less likely to incur an unpaid payment fee than a user in Decile 1. As more variables related to individual credit risk factors are included, *Socioeconomic Decile* loses significance, as factors related to individual credit behaviour likely subsume information based on broad postcode classifications.

Users with liquid savings balances exceeding $1,000 - represented by the indicator variable *Savings>1000* are considerably less likely (between 50 to 63%, according to the log-odds from Table 4) to incur unpaid payment fees. This group of users (around 11% of the pay-on-demand customer base in our sample) may simply be using pay-on-demand for convenience, or to address a minor liquidity mismatch between pay cycles, but appear be among the more successful users of the product. Users who always deposit their savings into the bank account (*Always Salary*=1) are, similarly, around 23% less likely to incur unpaid payment fees, based on the specification in model (1). In the models in Columns (2) to (5), *Always Salary* is interacted with *Income* (log(Income+1)) as income can be estimated accurately for these users based on amounts deposited into bank accounts. Generally, the coefficient of *Income* is negative, indicating that users with higher incomes are less likely to pay unpaid payment fees.[3] Not surprisingly, users with more regular and higher incomes are less likely to incur fees associated with the use of pay-on-demand.

The likelihood of a pay-on-demand user incurring unpaid payment fees is higher for those with a credit card (based on the results from specification (1) and (2) in Table 4. However, neither of these two models include information about the usage of the credit card. Model specifications (3) and (4) of Table 4 incorporate both prior credit card delinquency and an indicator variable for *Highly Utilised* credit card holders. The inclusion of these variables alters the sign of *CC Flag* from positive to negative. Holding a credit card, which in and of itself requires a credit check at application, and requires frequent servicing (and overdue payment fees itself), lowers the likelihood of incurring an unpaid payment fee. However, users who have missed one payment (*CC Flag * CC Delinquency Bucket 1+*) are only slightly less likely to pay unpaid payment fees than non-credit card holders. Users who have had multiple missed payments (*CC Flag * CC Delinquency Bucket 2+*) are more likely to be subject to unpaid payment fees. The coefficients of each of the *Delinquency Bucket* variables can be added to *CC Flag* itself,

[3]Although the coefficient on *Always Salary* is negative after including the interaction term, *Always Salary* users only need a very small amount of *Income* to be less likely to incur an unpaid payment fee. For instance, in column (6), the threshold value of *Income* is $e^{0.127/0.024} = \$198.34$.

noting that users who have been in Bucket 2 or higher will also have appeared in Bucket 1 or higher. From the specification in Column (3), the net coefficient for a credit card holder who has been in bucket 2+ is $(-0.599 + 0.444 + 0.525) = 0.370$, which indicates they are about 45% more likely to pay an unpaid payment fee. Incorporating the Highly Utilised indicator variable, credit card holders who have used more than 95% of their credit limit are only slightly less likely to incur an unpaid payment fee. In a similar vein, customers with hardship arrangements in other financial obligations also seem to struggle with pay-on-demand, evidenced by the significant and positive coefficient on *Hardship* in specification (4) and (5).

Users of higher risk grades have higher odds of paying an unpaid payment fee (and higher numbers of unpaid payment fees), as reported by specification (5) and (6) in Table 4. Users from a lower risk grade (belonging to grade 1 or 2) are much less likely to pay unpaid payment fees, whereas users from a higher risk grade (*Risk Grade 4*) are much more likely to do so. Providing an interpretation of the magnitude of the coefficients, holding all else constant, a user from grade 1 or 2 has only 16% and 44% the odds of paying an unpaid payment fee compared to a user from the median risk grade (*Risk Grade 3*). In contrast, a user from *Risk Grade 4* has 1.85 times the odds of incurring an unpaid payment fee compared the average bank customer. Although individuals in risk grade 5 are difficult to score (therefore may not be of a higher risk), they appear to be the least probable group to be a successful pay-on-demand user. According to the results of specification (4) and (5), pay-on-demand users that are classified into *Risk Grade 5* are 1.87 times as likely as an average bank customer to pay an unpaid payment fee, and on average they pay 1.199 times more unpaid payment fees every month in comparison.

The introduction of the risk grade variables significantly increases the model's predictive power t, evidenced by the change in pseudo R^2 from model 4 to 5 (from 0.046 to 0.120). Such predictability is mainly driven by the difference in the length of information that the bank and pay-on-demand providers analyse to assess credit risks. Pay-on-demand providers typically assess only two months of information, whereas the bank incorporates information of longer time to develop the risk grades. Performing credit checks may thus lead to a substantial improvement in loan profitability for pay-on-demand providers, due to an increased effectiveness of screening.

4.2 Who borrows more from pay-on-demand?

Next, we run OLS regressions on the amount borrowed from pay-on-demand platforms (*Net Trans Sum Loan*) within a month. In a similar vein to the previous section, we incrementally introduce more explanatory variables to each column. Column (1) only contains information that can be revealed by a preliminary inspection of the bank statement, and from columns (2) to (5) we include more explanatory variables including income (2), credit card utilisation status (3), other product co-holding information (4) and credit risks indicators (5). Table 5 presents the results of the regression on the amounts of withdrawals.

The results in Table 5 indicate that *Age* is a determinant of the intensive margins. In all columns in Table 5, the coefficients on *Age* is positive and significant, indicating that older people borrow more from pay-on-demand. Based on the result in column (1), on average, a ten year increase in age is associated with a \$17.14 increase in monthly wage withdrawn. Thus, while the product skews towards younger users, older groups access a greater amount of funds. Users from higher socioeconomic deciles similatly access greater amounts from pay-on-demand platforms. On the other hand, a significant and negative coefficient on *Gender* is reported in all columns, both before and after controlling for the customer risk grade. Males withdraw \$25.38 more wages in advance compared to female users, based on the result in Column (1).

In terms of financial stability, people with more than \$1,000 of savings withdraw a substantially greater amount of wages, suggesting savings are an important part of the pay-on-demand screening procedure. In Model (2), we only include the variables that pay-on-demand providers are likely to be able to access as explanatory variables. The results suggest on average people with more than \$1,000 of savings borrow \$27.893 more per month, or 11.12% more based on an average borrowing of \$250.73 per month. Similarly, users who always deposit their salaries into their savings account borrow \$67.403 more from pay-on-demand [4] as per Model (1), and users with higher incomes borrow more. As pay-on-demand claims to only let users access their earned wages in advance, it is reasonable that users with higher income can advance more of their wages.

Next, we examine the variables related to the credit card usage. All Columns of Table 5 evidence that people with a credit card tend to borrow more from pay-on-demand. In Column (1) of Table 5, which does not include the variables related to the credit card past delinquencies and utilisation rate, users with a credit card borrow \$36.514 more per month compared to non-credit-card users. When past delinquency and utilisation variables are included (in Columns (3) to (5)), the magnitude of the coefficients on *CC Flag* increases, as users with unsuccessful credit card usage history tend to withdraw less from pay-on-demand. Even after controlling for credit risk grades (Column (5)), customers with a credit card still borrow more compared to those without a credit card, regardless of their past delinquency record and utilisation status. Results from the specification reported in Column (3) indicate that both prior delinquency (Bucket 2+) and high credit card

[4] Although the inclusion of *Always Salary * log(Income+1)* turns the coefficient negative, the critical value at which users under *Always Salary* borrow less than users who are not under the same classification is very low. For example, in Column (5), the critical value is $e^{8.803/7.434} - 1 = \$2.268$.

	-Net Trans Sum Loan				
	(1)	(2)	(3)	(4)	(5)
Age	1.714***	1.623***	1.634***	1.773***	1.965***
	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)
Gender (Female = 1)	-25.377***	-24.149***	-24.060***	-23.405***	-23.344***
	(2.624)	(2.618)	(2.616)	(2.604)	(2.592)
Socioeconomic Decile	3.047***	2.959***	2.937***	2.721***	2.671***
	(0.46)	(0.459)	(0.459)	(0.457)	(0.455)
Savings>1000	28.375***	27.893***	26.292***	18.593***	8.190*
	(4.593)	(4.588)	(4.593)	(4.611)	(4.647)
Always Salary	67.403***	-8.091	-8.285*	-9.168*	-8.803*
	(2.608)	(4.978)	(4.974)	(4.957)	(4.923)
Always Salary*log(Income+1)		8.212***	8.195***	7.653***	7.434***
		(0.487)	(0.487)	(0.485)	(0.483)
CC Flag	36.514***	34.766***	66.193***	55.208***	50.838***
	(3.702)	(3.699)	(7.441)	(7.429)	(7.481)
CC Flag * CC Delinquency Bucket 1+			-10.846	13.503*	30.566***
			(7.929)	(8.004)	(8.031)
CC Flag * CC Delinquency Bucket 2+			-58.686***	-36.247***	-34.662***
			(9.071)	(9.152)	(9.150)
CC Flag * Highly Utilised			-19.707**	15.795*	-8.044
			(8.167)	(8.170)	(8.174)
Risk Grade 1					40.630***
					(4.873)
Risk Grade 2					22.453***
					(4.142)
Risk Grade 4					-31.532***
					(3.652)
Risk Grade 5					-50.132***
					(3.708)
Personal Loan Flag				49.154***	44.326***
				(3.982)	(3.987)
Hardship Flag				-74.141***	-45.913***
				(3.646)	(3.947)
Benefit Flag				-41.557***	-41.964***
				(5.350)	(5.338)
Constant	150.367***	153.404***	153.464***	156.977***	159.360***
	(5.111)	(5.102)	(5.100)	(5.147)	(5.512)
N	49,866	49,866	49,866	49,866	49,866
R^2	0.025	0.030	0.032	0.043	0.052
Adjusted R^2	0.025	0.030	0.032	0.042	0.051
Residual Std. Error	284.567 (df=49859)	283.785 (df=49858)	283.552 (df=49855)	282.033 (df=49852)	280.689 (df=49848)
Notes:					***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 5: Predictor for loan amount

Notes: This table presents the OLS regression that uses the demographic, socioeconomic, other product co-holding and credit risk variables to predict the amount of wages accessed in advance using pay-on-demand. Heteroeskedasticity consistent standard errors of the coefficients are included in the brackets.

utilisation lowers the amount accessed on platforms. Pay-on-demand credit card holders borrow between $35 and $55 more than pay-on-demand users without a credit card.

Similar to users with a credit card, users holding other credits products, such as a personal loan, also borrow more than non-personal-loan holders. As shown in Column (4) of Table 5, users with a personal loan borrow $49.154 more per month than users without a personal loan. Due to concerns that this correlation is driven by users with a personal loan are safer customers, we control for the credit risks variables in Column (5), and we obtain quantitatively similar results. Columns (4) and (5) also indicate that users receiving benefits on average borrow around $42 less than those not on benefits.

Column (5) of Table 5 has shown that users with higher customer risk grades borrow smaller amounts from pay-on-demand. Compared to a pay-on-demand user from Risk Grade 3, users from grade 1 and 2 borrow a marginal $40.630 and $22.453 per month, whereas users from grade 4 borrow $31.532 less. Users who are difficult to rank (risk grade 5) borrow $50.132 less per month. Although the pay-on-demand providers do not perform a credit check, Column (5) does imply that their proprietary algorithms that perform only bank statement analysis are somewhat predictive of amounts borrowed.

Overall, the results here are consistent with the results in Table 4. In general, users that have incurred unpaid payment fees use pay-on-demand less due to losing access to pay-on-demand and being assessed as riskier customers by the lenders. Hence, most of the variables that are positively related to unpaid payment fees are negatively related to the amount borrowed.

5 Discussion and conclusion

In this paper, we have analysed the effect of the introduction of pay-on-demand platforms into Australia. This Fintech product allows users to access their next pay cheque in advance, subject to the charge of a 5% transaction fee per use. Although low-cost access to credit may improve customer welfare, achieving the intended benefit requires adequate financial literacy (Gerrans et al., 2022). In Australia, pay-on-demand products are not regulated under the NCCP Act as credit, and are exempted from the responsible lending guidelines.

By comparing the demographic and socioeconomic information of pay-on-demand users with those of an average Australian and Buy Now Pay Later user (see Australian Bureau of Statistics (2022a) and Boshoff et al. (2022)), we have found that on average, users of pay-on-demand are heavily skewed towards younger males, with smaller savings balances, and lower incomes. Pay-on-demand users are from lower socioeconomic areas, and of higher credit risk level, compared to an average bank customer or the sample of

BNPL users. Moreover, we show that only a small proportion of pay-on-demand users (17.1%) have a credit card with the bank. Of the credit card holders, 73% have utilisation rates above 95%, and around 70% have been delinquent on their card in the previous 12 months. Thus, pay-on-demand users with credit cards demonstrate signs of financial stress.

We have also shed light on the subset of pay-on-demand users who paid an unpaid payment fee (a dishonour fee charged by the bank for a failed direct debit). Although pay-on-demand claims to charge no hidden cost besides the "transaction fee," the use of pay-on-demand is associated with significant unpaid payment fees. Almost half (46.5%) of pay-on-demand users incurred at least one unpaid payment fee in our detailed one-month sample of transactions. Among the sample of unpaid payment fee payers, the average dollar amount was $24 in dishonour fees. This cost accounts for an 11.85% increase in charges associated with the use of pay-on-demand, when expressed as a proportion of total amount borrowed.

In empirical tests, we examined whether there are structural differences between users who paid and who did not pay unpaid payment fees. Users who pay unpaid payment fees, on average, have lower savings balances, smaller incomes, and reside in lower socioeconomic areas. Unpaid payment fee payers are less likely to deposit their wages into their savings account and are around three times more likely to be in financial hardship. Based on the bank's internal credit score, users who pay an unpaid payment fee are twice as likely to be in the two highest risk bands than users who do not pay unpaid payment fees (62% vs. 31%). Arguably, the group of unpaid payment fee payers would be able to be identified in advance if pay-on-demand platforms engaged with the credit bureau system (i.e., by checking credit scores).

Users and providers of pay-on-demand, and traditional financial institutions are all likely to benefit from the employment of credit checks. Constrained borrowers may be able to save on unpaid payment fees; hence, their overall financial resilience may improve. Other users of credit bureau information (i.e., banks and other lenders) will also benefit from an improved transparency in credit scores, through a reduction in information asymmetry. With access to credit bureau data, pay-on-demand lenders could also receive a substantial improvement in loan profitability by improving screening accuracy. For example, we document a substantial increase in pseudo R^2 of a logistic regression model predicting unpaid payment fee payers with the inclusion of product holding and risk grade variables (i.e., variables which would be easily observed with credit bureau information), compared to only including a set of postcode and demographic variables. We also show that around 40% of pay-on-demand users do not earn a consistent wage, and those that do not are more likely to be unpaid payment fee payers. Stricter underwriting processes are likely to help find pay-on-demand platforms repeated users, while helping to exclude borrowers who are likely to miss payments.

The benefits of a credit check are likely to be greater over time, as credit bureaus in Australia incorporate more information into the credit report. For instance, starting July 1^{st} of 2022, *Equifax*, *Experian* and *illion*, the three largest credit reporting body in Australia, have started to include the financial hardship arrangements into credit reports. It is likely to be prudent for pay-on-demand providers to screen applicants who are already in hardship, but this would require their engagement with the bureau system. Nonetheless, the benefit of better screening comes at the cost of a reduction in loan volume to the pay-on-demand providers, as a large proportion of the borrowers at pay-on-demand may be of low credit quality.

Pay-on-demand lenders, while avoiding responsible lending obligations, can only charge the flat 5% transaction fee to customers. As there is no ability to alter interest rates (i.e., to charge riskier customers more), to ensure the pay-on-demand business model remains profitable requires customers to repay their loans (and most likely, be repeat users). The amount that users borrow each month is largely consistent with the eligibility criteria of using pay-on-demand. Customers that would be generally considered safer by pay-on-demand providers (higher income, higher socioeconomic decile), on average, borrow a larger amount.

Future research should examine in greater detail the motivation for people to take out a pay-on-demand loan. Users could be surveyed regarding financial literacy and whether the lack of credit check is attractive. A limitation of this research is also that we are unable to see the loan purpose, or the other spending habits of pay-on-demand users. Pay advancements may be spent on purchasing essentials (or meeting other credit obligations), which may be beneficial to the borrowers. Alternatively, proceeds may be used to fund excessive consumption and entertainment, like the case with payday loans (Cuffe and Gibbs, 2017). Understanding the broad spending patterns of consumers who use pay-on-demand will help determine whether the product encourages excessive spending, or facilitates consumption smoothing. It would also be interesting to track users with a clear pay cycle, and identify at which point pay-on-demand is most commonly used (as in Murillo et al. (2022), but for a direct-to-customer model). This would allow for a deeper investigation into 'payday effects' for Australian pay-on-demand users. A separate line of enquiry could explore the longer-term impact of using pay-on-demand. If repeated use is associated with a decline in financial well-being (e.g. through a bureau score), it would likely strengthen the case for regulation. Answering these questions will contribute more empirical evidence on why people use pay-on-demand and how pay-on-demand is used.

6 Appendix

Variable name	Definition
Age	A customer's age in years.
Always Salary	An indicator equal to one if the customer's salary type is always earning a salary.
Benefit Flag	A dummy variable equal to one if the customer is unemployed and is receiving an unemployment benefit.
CC Delinquency Bucket 1+	An indicator equal to one if the customer has missed a payment in the last 12 months. For non-credit card users, this value is set to zero.
CC Delinquency Bucket 2+	An indicator equal to one if the customer has missed a payment in the last 12 months with more than 30 days overdue. For non-credit card users, this value is set to zero.
CC Flag	A dummy variable equal to one if the given customer has a credit card, and zero otherwise.
Customer Risk Grade	The risk grade is a categorical variable assigned to the customers, based on the quintile that their behavioural scores are in. The scores are given based on the bank's internal grade algorithm. The higher the risk grade, the higher the risks of the customers. For example, customers of grade 2 are riskier than people in grade 1. Grade 1 to grade 4 represent customers from the least risky to the most risky group. Grade 0 is given to customers who are yet to be scored, and grade 5 is given to customers who are difficult to score. A grade 5 can be given, if the input value to the grading algorithm exceeded the allowable range.
Deposits Savings Balance	The balance of the customer's deposit savings account, denoted in Australian dollars.
Gender	A dummy variable equal to one if the customer's gender is female, and 0 otherwise.
Hardship Flag	A dummy variable equal to one if the customer is labelled as having a financial hardship by the bank.
Highly Utilised	A dummy variable equal to one if the customer's credit card utilisation rate is over 95%. For customers without a credit card, this value is set to zero.

Income	The estimated yearly income of the customer. This estimate is produced by the bank that provided the data through an analysis of the users' transaction details and bank statements.
Net Trans Loan	The total number of loans that a customer has borrowed from *BeforePay* and *MyPawNow*.
Net Trans Payments	The total number of payments from a customer's account to *MyPayNow* and *BeforePay*, after excluding those transactions that are reversed due to insufficient balance.
Net Trans Sum Loan	The total dollar value of the wages that a customer has borrowed from the pay-on-demand borrowers.
Net Trans Sum Payments	The total dollar value of payments that a customer has made to pay-on-demand lenders, after excluding the transactions that are reversed.
Never Salary	An indicator variable equal to one if the customer has not received any salary.
Num. Transactions	The total number of payments to a pay-on-demand providers in a customer's transaction data in a given month.
Num. Unpaid Payment Fees	The total number of unpaid payment fees that a customer has incurred in a given month.
Personal Loan Flag	A dummy variable equal to one if the customer has an outstanding personal loan with the bank.
Risk Grade X	A dummy variable equal to one if the customer's risk grade is equal to X. For instance, Risk Grade 1 is equal to one if the customer's risk grade is 1.
Salary Ceased	An indicator variable equal to one if the customer used to earn a salary, but the salary has stopped.
Salary Switching	An indicator variable equal to one if the customer has switched salary according to the bank's record.
Savings > 1000	An indicator variable equal to one if the customer's savings balance is greater than $1,000 at the end of the month.
Socioeconomic Decile	The socioeconomic decile of a customer's address. The decile is calculated by matching the postcode of the address with the Australian Bureau of Statistics (ABS) "Socioeconomic Index for Areas" Index of Advantage and Disadvantage (2016) ranking of every postcode. The decile ranges from 1 to 10, with 1 representing the poorest socioeconomic areas, and 10 meaning the affluent areas.

Unpaid Payment Fee Flag	A dummy variable equal to one if the customer's Num. Unpaid Payment Fees is greater than 0.
Utilisation Rate	The ratio of the customer's credit card balance to the maximum credit limit of the credit card.

Table 6: Variables definitions

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