THE UNIVERSITY OF SYDNEY

The University of Sydney

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

Author:
Borui Li

Supervisor:
Andrew Grant

STATEMENT OF ORIGINALITY

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at the University of Sydney or at any other educational institution, except where due acknowledgement is made in the thesis.

Any contribution made to the research by others, with whom I have worked at the University of Sydney or elsewhere, is explicitly acknowledged in this thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the projects design and conception or in style, presentation and linguistic expression is acknowledged.

Borui Li

February 27, 2023

ACKNOWLEDGEMENTS

I would like to acknowledge and give my sincerest thanks to my supervisor Andrew Grant who made the thesis possible. Without his continuous guidance, feedback and advice, I would not be able to produce a work of such quality. I would also like to thank the Commonwealth Bank of Australia (CBA) for providing the data for this research and their efforts in organising the research. A particular shout out to Dini Ding, who spent an incredible amount of time assembling and cleaning the data. Thank you.

I also owe a debt of gratitude to the honours staff and cohort. I would like to say thank you to my honours lecturers who provided me with the theoretical backgrounds to carry out the research, the honours staff who made this an enjoyable year, and the BUSS4001 research proposal marker who provided valuable feedback on the thesis. Thank you to all the friends I made along the way.

Finally, I would like to thank my parents and friends, who provided invaluable support that carried me throughout the honours year and proofread my thesis over and over again.

Abstract

This thesis examines a novel Fintech lending product in Australia named pay-on-demand. This product claims to let its users access their wages in advance, at a flat "5% transaction fee" without any hidden cost. Using the transaction data of customers at a major Australian bank, I have found that, on average, pay-on-demand users are usually more financially constrained compared to the general public. They tend to live in poorer socioeconomic regions, earn lower incomes, have less savings, and lack alternative access to credit due to past delinquency records and damaged credit reputation. The product is predominantly accessed by younger males.

Almost half of the users are additionally paying an unpaid payment fee, which is a cost imposed by the banks due to a failed direct debit request and represents a hidden cost of using pay-on-demand. An average user of pay-on-demand will be charged unpaid payment fees 2.24 times a month, which given the average loan size of $250.73, increased the Effective Annual Rate by 54%. On average, users who are from poorer socioeconomic region, have less saving balance, earn lower wages, have high credit risks, and are in hardship are more likely to pay an unpaid payment fee.

Finally, I found that users with lower savings balance use pay-on-demand more frequently, although they borrow less in total because they are deemed riskier by pay-on-demand lenders. These users paid more unpaid payment fees, which worsened their financial status and forced them to borrow more from pay-on-demand to guard against future cash flow mismatches.

Overall, the results highlight the importance of a strict underwriting procedure. Pay-on-demand is excluded from the responsible lending criteria, so lenders do not perform a credit check. If a credit check is performed, constrained borrowers would be better off, because they could save on unpaid payment fees and their financial resilience would improve.

Contents

1 Introduction

Australians suffered a deterioration of financial resilience from COVID-19. The Australian Bureau of Statistics (2022b) found that one in six households could not raise $2,000 within a week, while 5.4% of households would not even be able to come up with $500. Thus, a significant proportion of Australians are may need short-term funding in the case of an unexpected liquidity need.

The liquidity shortfall faced by Australian households is a product of not only of a lack of income, but also a mismatch in the timing of cash flows. Those who live 'paycheque-to-paycheque' 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 '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. Casual workers or those who receive volatile paycheques (e.g., freelancers) are particularly vulnerable to a cash flow timing mismatch.

Pay-on-demand services such as *BeforePay* and *MyPayNow* are short-term Fintech credit products that have recently entered the Australian market. Also known as 'earned wage access (EWA)' products, 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 their next paycheque, the amount owing is automatically withdrawn from the borrower's linked bank account. Users with volatile paycheques would be able to smooth their cash inflow by borrowing from their future pay cycle, which may alleviate the payday effect.

Pay-on-demand products have experienced significant growth in the past two years, as workers have become more and more interested in receiving their wages at the time of their choosing (Visa, 2019). This rapid development raised concerns about the impact of using pay-on-demand, due to its qualitative similarities with payday loans (e.g., Jeong

(2021)), which have been criticised as potentially predatory.

Other providers of credit are also interested in the demographics of users of pay-on-demand, as the behaviour of pay-on-demand users may be reflective of their underlying credit risks. In Australia, pay-on-demand services are not regulated as credit products, as they do not charge interest like traditional payday loans or pawnshop loans. Hence, pay-on-demand lenders are not required to perform a credit check under responsible lending guidelines. This limits their interaction with the credit bureau system, which effectively withholds private information related to product usage from other market participants. 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 thesis 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, what are the demographics of pay-on-demand users? Do pay-on-demand users exhibit signs of credit risk? Second, what proportion of pay-on-demand users use the product successfully? Third, in the cross-section of pay-on-demand users, are frequent users considerably riskier? Our data set enables us to directly observe the amount and frequency of access to pay-on-demand, which makes it ideal for the purpose of answering these three research questions.

I 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, which is consistent with the advertising strategy of the product. 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.

I show that almost half of users have incurred more than the simple "transaction cost" when using pay-on-demand. These 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, is less likely to have a credit card, and is more likely to be in financial hardship. Those who incur fees exhibit higher credit risk, measured by the bank's internal credit scoring algorithms, and are more likely to have had prior delinquencies on their credit cards and high utilisation rate.

In terms of the intensive margins of using the product, pay-on-demand customers that incur fewer unpaid payment fees, on average, borrow a larger amount. Hence, factors that would otherwise predict a higher value of unpaid payment fees would predict a smaller amount borrowed from pay-on-demand platforms. Alternatively, when investigating the frequency of use, it is found that users who have low saving balances borrow less often from pay-on-demand, but borrow a larger dollar amount on each occasion. This supports the view that pay-on-demand is used to manage short-term liquidity mismatches.

This study relates to several stands of literature. Firstly, 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, this thesis examines the viability of using pay-on-demand as a potential lower-cost replacement for payday loans.

Second, this thesis is related to the 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 thesis 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.

Finally, this research adds to the literature on 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 the 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. Through studying the adverse outcomes for both the lenders and the borrowers due to not performing a credit check, this thesis further contributes to this area of research by highlighting the importance of transparency in evaluating the credit risk posed by users.

The results of the research will also be important 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 means 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 which is not available to other lenders, reducing the transparency of credit bureau data (Liberman, 2016). We potentially aid in the 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 and 3 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. In Section 4, I developed the hypothesis for the research questions based on the existing theories and extant literature. Section 5 and 6 outline the data and the research design employed by this research. In Section 7, I drew out a stylised model that explains the operation of pay-on-demand and conducted a sensitivity analysis on the profitability of the lenders. Section 8 reported the results produced by the research design, and finally, Section 9 will discuss these findings and conclude the research by pointing out future directions for research in the field of pay-on-demand.

2 Institutional Background

2.1 Use case and market size

Pay-on-demand services, also called earned wage access (EWA) 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 paycheque, the amount owing is automatically withdrawn from the borrower's linked bank account.

Consider a waiter at a restaurant who works a single shift one week, but five shifts the following week. A weekly pay schedule means the waiter will receive the wages for only one shift by the end of the first week. This may leave the employee with insufficient money to buy essentials or to fulfil other financial obligations. Suppose instead that the waiter is able to receive payment immediately following their shift. Then there would be no liquidity issue in the second week. Pay-on-demand aims to smooth out the timing mismatch for such consumers.

Due to income and expense timing mismatches, individuals with volatile income tend to spend a large proportion of their income upon being paid (Gelman et al., 2014). Pay-on-demand targets this group of individuals by allowing them to smooth out their income, thereby alleviating the payday effect that Gelman et al. (2014) has documented. According to the replacement prospectus by *BeforePay*, the key target customers of theirs are the approximately 5.3 million people within the 9.5 million employed individuals aged from 20-54 years old, who can be benefited by short-term, non-revolving credit access.

Due to the Fintech nature of the product, pay-on-demand seeks to target a subset of the group mentioned above: the tech-sophisticated digital natives. As a result, the product has attracted a high proportion of young people, similar to other Fintech lending products like Buy Now, Pay Later.

> *Beforepay's platform appeals to a broad cross-section of society, although has particular appeal to those who are more likely to seek alternatives to other traditional forms of credit, are digital natives and are leading adopters of the 'on-demand' thematic.*

An example of how pay-on-demand may be used is shown in Figure 1. Suppose a customer is paid every two weeks. In May 2022 there are two paydays, May 5$^{\text{th}}$ and May 19$^{\text{th}}$. Individuals with little savings may not have the cash to cover any unexpected cash shortfalls, such as car repairs or unexpected health expenses. Without pay-on-demand, they will need to wait until the second payday to cover these expenses; however, the deferral of these expenses could be costly. Instead, they may access \$100 of their wages receivable to cover the unanticipated cash shortfall and repay them later. On their next payday, the employee will be required to pay \$105, which will be deducted automatically by the lenders. The borrowers may also have the option to split the \$105 into three \$35 direct debit payments if using *BeforePay*.

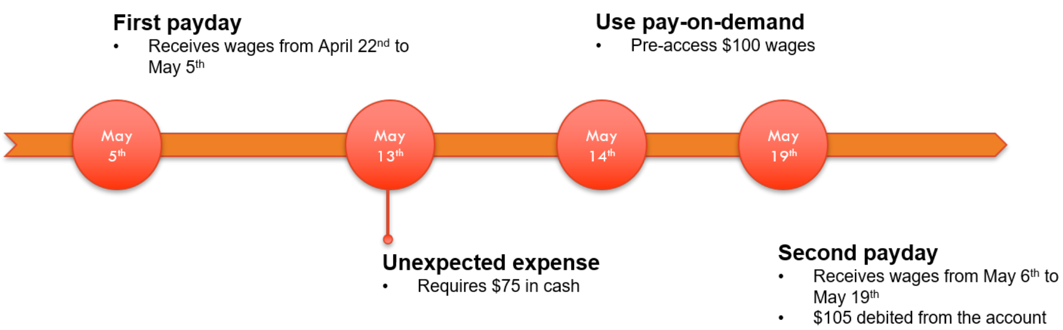


Figure 1: Pay-on-demand example usage

The industry has experienced significant growth since August 2020 (see Figure 2). 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.

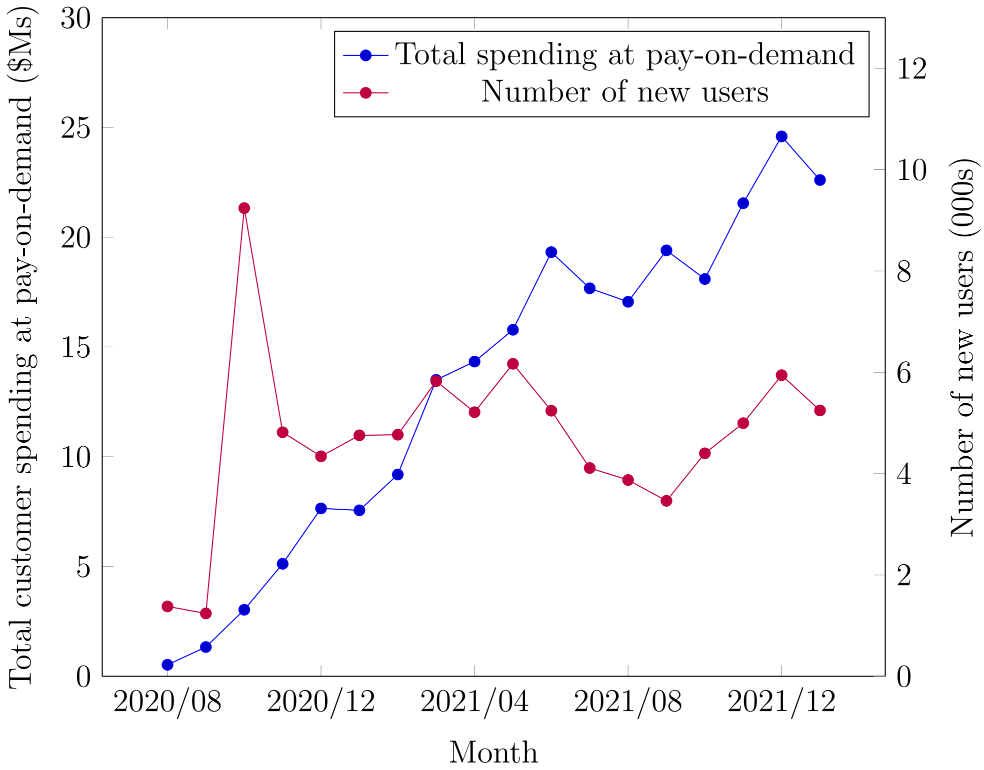


Figure 2: Size and growth of pay-on-demand market

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 CBA 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. I 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.

The rise in the demand for the product corresponds to the casualisation of workforce in Australia. 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 Terms of use

A summary of key terms of pay-on-demand is provided in Table 1. 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). The purpose of accessing bank account transaction data is to confirm the employment status of a borrower, as wage advancement products are limited to consumers who are paid regularly (weekly, fortnightly, or monthly) and earn a wage of at least \$300 after-tax (for BeforePay) or \$450 after tax (for MyPayNow). Both providers utilise proprietary algorithms, based on an analysis of bank account transactions (including income, expenses, and transaction type) and previous repayment behaviour to determine the amount that a consumer can advance from their upcoming wage. The maximum amount that a customer can advance using BeforePay is $\$1,200$ ($\$1,250$ on MyPayNow), which can be repaid either in instalments over a period of up to four weeks (for BeforePay) or at the next paycheque (for MyPayNow). The maximum loan value will start low, and increase gradually if the customers demonstrate good repayment behaviours.

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 interest. By charging not charging interest, neither *BeforePay* nor *MyPayNow* are subjected to the National Consumer Credit Protection Act 2009 (NCCP). The NCCP Act mandates explicit lenders to apply for a credit license; hence the regulators have the direct power to supervise the conduct of these lenders, such as mandating the responsible lending criteria or a credit check (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. Instead, the Fintech providers choose to rely on their proprietary algorithm to assess the creditworthiness of their potential customers, broadening their targeted range of users.

2.3 Business models

There are two major models of pay-on-demand services, the direct-to-customer and the direct-to-business model (Hawkins, 2021). In the former model, the providers of pay-on-demand lend directly to the employees and deduct the advanced wages directly on the next payday from the employees' accounts. The lenders rely on the information provided by the employees to assess risk. This model of operation is very similar to a Small Amount Credit Contract (SACC), such as payday lending.

In the direct-to-business model, the providers either serve as a technological platform to support the employees to access wage receivables, or the providers fund the advancement themselves, after which the employers deduct from the employee's pay cheque and reimburse the providers. This model is popular amongst gig-work employers. An example of this model is the partnership between *Walmart* and *PayActiv* to increase the frequency of pay to the employees at *Walmart*. Similarly, rideshare app *Uber* set up earned wage access for their drivers, who operate flexibly. This model is popular in the US (e.g., *PayActiv* or *OnDemand Pay*), and is also used in Australia. For example, *WageStream* is used by employers in the care (e.g. Bupa), hospitality (e.g. Adecco, Carnival Cruises), and retail sectors (e.g. Hungry Jacks, Freedom) to improve the pay flexibility for employees. In some cases, employers cover the cost of releasing wages early - but typically the employees pays.

The two models differ significantly in terms of the risks they impose on customers. In the direct-to-business model, the wages are deducted from the employee's paycheque before the employees even receive their wages. As a result, pay-on-demand lenders effectively have the most prioritised claims on the employees' wage receivables. This eliminates the option for employees to default strategically, which prior research has shown to be valuable in managing liquidity, especially for low-wealth individuals (e.g., see Tiruppatur et al. (2010), Guiso et al. (2013) and Gerardi et al. (2018)). For example, an individual that has recently advanced $500 to repair their window might also require another $100 to afford the medicines he or she needs, and being able to break the promise to pay-on-demand may be a useful tool to access that $100. In contrast, promises to repay other SACC such as credit card debts or payday loans are relatively easy to break.

In the direct-to-customer model, the employees receive their wages in their bank accounts, and the lenders will try to estimate the precise time that employees receive their wages, so they debit the account immediately at the time of payment. This collection mechanism is less efficient than the one used by the direct-to-business model, as theoretically the employees can transfer the money out during the narrow time gap between receiving wages and the direct debit (Hawkins, 2021). Although it enables the borrowers to strategically miss payments, this option is usually costly (incurring unpaid payment fees) and accompanies hidden costs as listed in Section 2.4.

In Australia, both of the two major pay-on-demand providers *MyPayNow* and *BeforePay* operate using the direct-to-customer model. Both companies directly provide wage access to the borrowers and deduct the wages from the employee's bank account directly. Hence, this research focuses on studying the direct-to-customer model.

2.4 Mitigating credit risks

In order to circumvent the NCCP Act, pay-on-demand providers in Australia operate on very narrow margins, which are a maximum of 5% of the total amount borrowed. As reported in the Australian Financial Review (Sier, 2022), the 5% transaction fee charged by BeforePay may be underpricing risk. Two of the major SACC lenders in Australia, *Nimble* and *Money Plus* charge a 4 per cent monthly fee plus a 20% establishment fee. In comparison, with an average loan size of around \$260, BeforePay makes a gross return of \$13 per loan (Sier, 2022). Unlike other Fintech lending products like Buy Now Pay Later (e.g. Afterpay charges late fees, Zippay charges account fees), pay-on-demand providers in Australia charge zero late fees or account fees, and rely solely on the flat 5% transaction fee.

To aid the exposition, consider the case of a 3% default rate (assuming no recovery), which is reportedly the target for BeforePay (as in their pre-IPO statements). Suppose that the platform's funding and fixed costs are 1.25% per loan then their $Net\ Profit$ per loan is

$$\text{Net Profit} = (1 - 0.03)(0.05)(260) + 0.03(-260) - 1.25\%(-260) = \$1.56 \tag{1}$$

With limited scope under the regulations to alter their transaction fees, BeforePay would need to ensure a loss rate of 3.57% or lower to remain profitable, ceteris paribus. This is a low level of defaults considering the risky nature of the customer base. An essential part of the strategy of pay-on-demand platforms is thus to minimise credit losses by maintaining a low default rate.

Given this regulatory environment, credit risk management for these platforms is a vital part of operations. The first strategy through which pay-on-demand providers reduce credit risk is the use of transaction scoring to screen debtors. The ultimate goal is to shortlist all the credit-worthy customers, and filter out all the likely bad risks. Pay-on-demand lenders use bank statements and previous transaction behaviour to screen debtors and determine the value that can be advanced. The reason for accessing bank statements instead of performing a credit enquiry is that, according to *MyPayNow* managing director, Bronson Powe, argued that "credit scores vary between the agencies that compile them, and may contain outdated information" (Jeong, 2021), and so scraping transaction data is preferred. As credit scores are updated monthly, the analysis of transaction-level data should aid in the credit assessment process.[1] The use of transaction scoring also enables credit-damaged customers or those without credit scores to obtain a wage advancement.

To further control credit losses, users are permitted to borrow a only small amount on first use, and are encouraged to repay on time to increase their available funds. Under an environment of asymmetric information, the transaction scoring algorithm cannot perfectly identify credit-worthy customers from one who is not credit-worthy, so the providers need to rely on other post-screening signals to better differentiate between them.

In the Australian pay-on-demand industry, the customers need to demonstrate a long history of successful usage of pay-on-demand to be considered more credit-worthy. The limit in loan sizes offered to customers by the pay-on-demand platforms is dynamic, similar to BNPL platforms. In other words, borrowers start with a low limit (approximately \$100, but anywhere between \$50 and \$800 according to the BeforePay FAQ), which gradually increases after successfully completing payments on transactions. Those who miss payments are unable to obtain further funding until their balance owing has been repaid, while subsequent limits are slashed. Thus, while information is not shared with credit bureaus, pay-on-demand customers have an incentive to repay loans in order to retain access to future credit. For customers with poor credit histories, maintaining a relationship with pay-on-demand lenders is particularly valuable, as they will have limited outside options.

[1] Credit bureaus, including *illion* and *Equifax* have developed alternative scoring systems, more suited to take into account short-term loans. For example, the Equifax One score utilises machine learning along with real-time updating and feedback streamline and improve credit decisions. Similarly, illion's Transaction Risk Score (iTRS) incorporates information from a consumer's income and expense transactions to facilitate more accurate credit decisions, particularly for people with 'thin' credit files.

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 3, I 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. This is explained by the repeated use of the borrowers. Earlier sign-ups mean the users have 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.

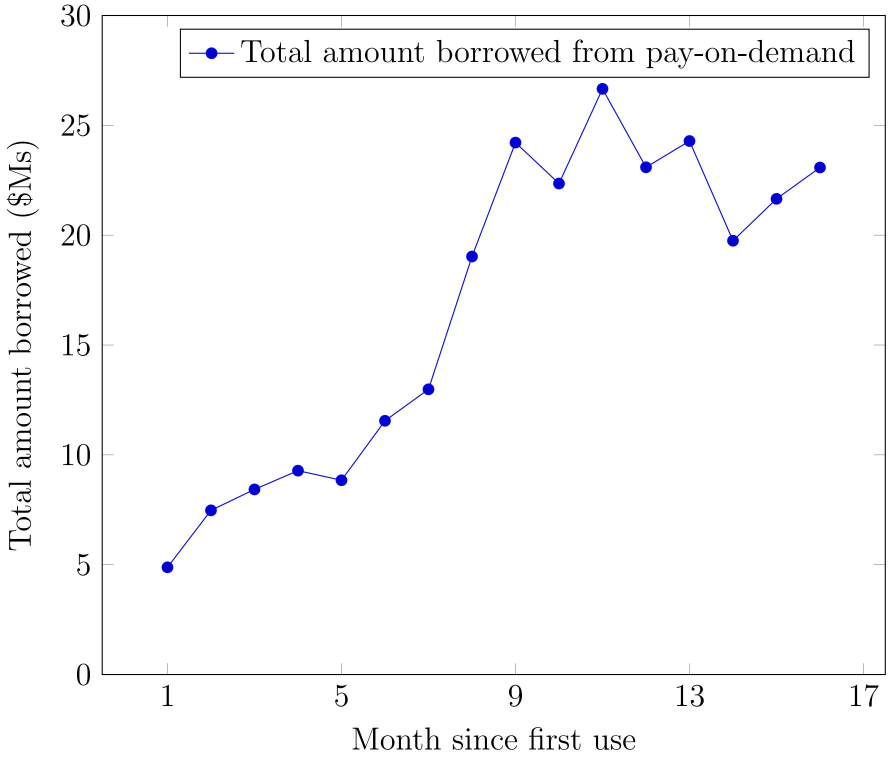


Figure 3: Use of pay-on-demand over time

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 2.

Figure 4 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 the users access pay-on-demand repeatedly. 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, I 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.

The collection mechanism of pay-on-demand is also important to the success of the industry. Pay-on-demand providers establish a salary link, the ability to directly deduct money from the employees' accounts to ensure repayments. This link is what enables Fintech lenders to remain a going concern despite charging a low interest rate (Baker and Kumar, 2018).

In the direct-to-customer model, lenders mandate direct debit, and only a debit account can be used by a borrower to receive wages and make repayments. Using past transaction history and past pay cheques, pay-on-demand providers can estimate the time that their users are paid their wages, thereby debiting the account directly at the time of payment. Assuming their estimates are accurate, the salary link 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.

The functionality of salary link is also imperative to the borrowers, as a failed direct debit will incur a dishonour (unpaid payment) 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

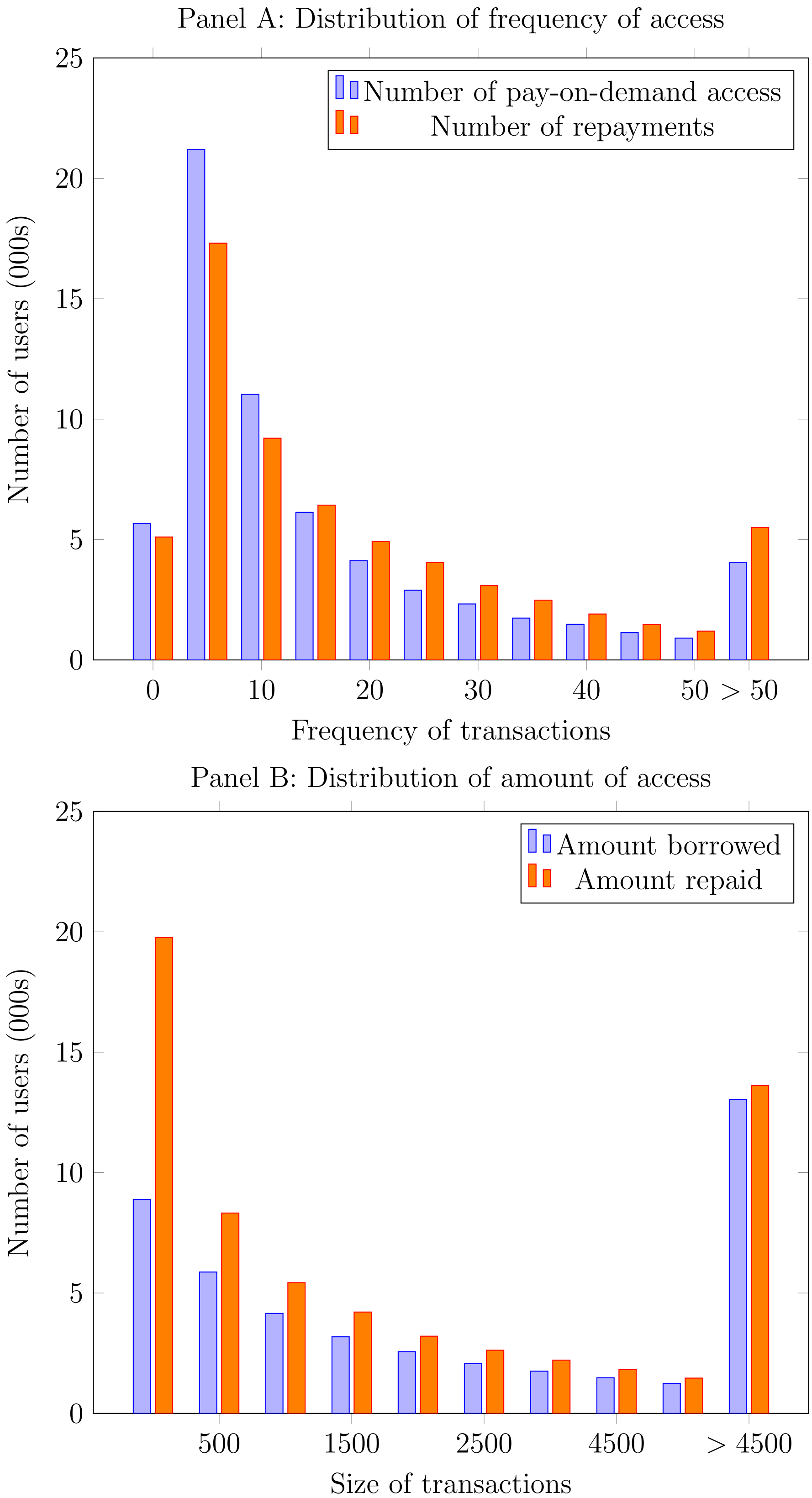


Figure 4: Key user characteristics of pay-on-demand

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.

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. [2] 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 paycheque 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 5, I 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 unpaid payment fees are paid by these users.

[2] A typical pay-on-demand loan with an interest rate of 5% over a period of two weeks would imply an equivalent annual rate (EAR) 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%.

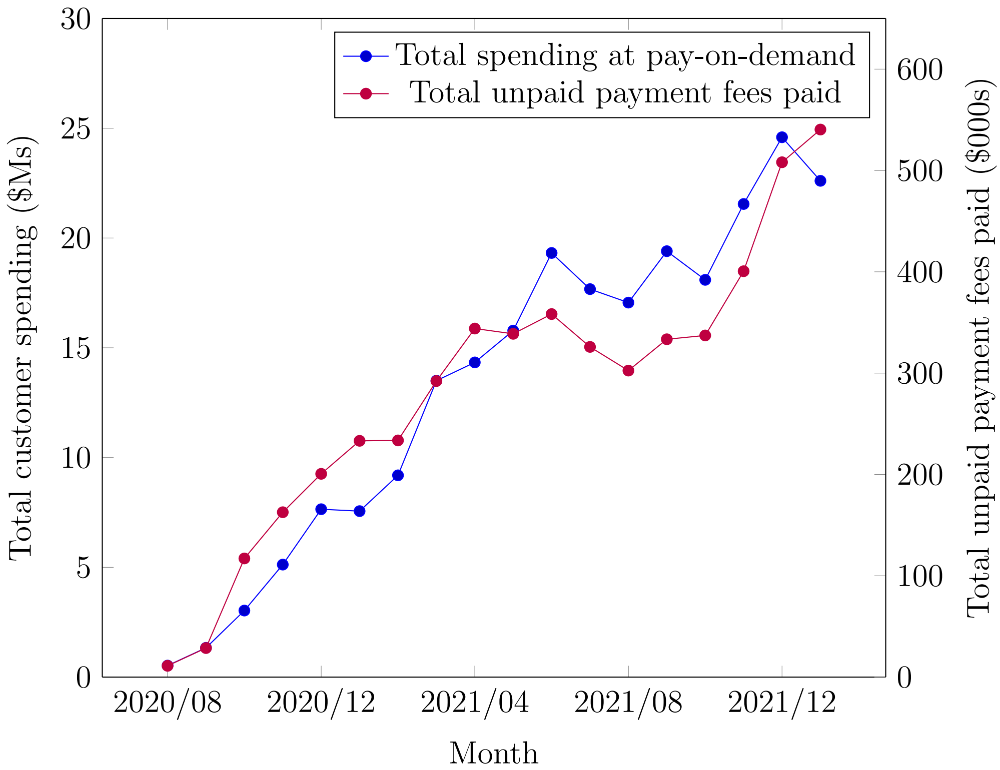


Figure 5: Customer spending and unpaid payment fees

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 2.

3 Literature Review

3.1 Theories of credit contracting

Stiglitz and Weiss (1981) originated the application of information asymmetry theory under a credit market context. Relying on the assumption that lenders cannot distinguish between borrowers of different levels of creditworthiness and limited liability of loans, banks will set an interest rate level for all borrowers. Since the borrowers possess more information about their riskiness of themselves than the lenders, raising interest rates will reduce the gross return of borrowers by disproportionately attracting customers of a higher risk level.

Two problems arise because of the said information asymmetry. The first problem is adverse selection, that the willingness to accept a certain interest rate level signals a bad quality of the borrowers. As a result, charging higher interest rates may decrease the creditworthiness of the applicant pools. The second is the moral hazard problem, that borrowers who receive the loan will use the proceeds opportunistically instead of in a way mutually beneficial for the borrowers and the lenders. Examples of opportunism include investing in riskier projects (see Steijvers and Voordeckers (2009)) and debt overhang (see Myers (1977)). The important implication of their paper is that there will be an interest rate $\hat{r^*}$ that maximises the expected return of the lenders, and there will be welfare-destroying credit rationing by the lenders, leaving many individuals unable to obtain credit access even at equilibrium.

Since Stiglitz and Weiss (1981) outlined asymmetric information as a key problem in credit contracting, extant theoretical literature motivated a variety of methods to alleviate the problem. Since raising interest rates may actually reduce the gross returns of the lenders who face information asymmetry, financial institutions need to use other loan terms and conditions to discriminate amongst the borrowers. In summary, there are two goals that lenders seek to achieve. The first is to learn more about the lenders' quality *ex-ante* to reduce adverse selection, and the second is to discourage opportunistic behaviour *ex-post* to alleviate moral hazard.

Related to the goals of mitigating adverse selection, researchers have identified two mechanisms: Spence (1973)'s theory of signalling, which involves the informationally advantageous party revealing information about themselves, and Stiglitz (1975)'s theory of screening, in which the informationally disadvantageous party seeks to obtain information about the other party. Extant literature has motivated various signalling devices, such as the size of loan contracts (e.g., Milde and Riley (1988)) and the amount of collateral (e.g., Bester (1985)). More importantly, Kawai et al. (2022) has found empirical evidence that in an online lending environment, signalling can restore most of the welfare loss induced by adverse selection. Boot and Thakor (1994) additionally asserted that in a repeated lending market, previous successful contracts are can signal the borrower's credit quality. Lenders are able to leverage these signals to exploit the differences in the applicants' marginal rates of substitution, so they can learn about the intrinsic creditworthiness of the applicants. On the other hand, lenders may screen borrowers by obtaining extra information that relates to their creditworthiness. Cao and Gruca (2005) has shown that companies may implement effective customer relationships management (CRM) to screen potential users during their advertising, so they service more profitable customers. Additionally, Einav et al. (2013) found that in high default risk and low recovery markets, screening based on credit scores can substantially improve the profitability of the lenders. The improvement is a result of reducing lending to bad borrowers due to more stringent down payment requirements and expanding credit to good borrowers through more generous financing.

On the moral hazard side, researchers have found that the size of collateral (see Barro (1976), Bester (1985) and Boot and Thakor (1994)), loan maturities (see Stiglitz and Weiss (1983)) and covenants (see Carey et al. (1993)) are all useful terms that can be modified to restrict borrowers' flexibility and align the interests of lenders and borrowers, thereby mitigating the moral hazard problem. Moreover, in a repeated lending market, the rights of the lenders to terminate contingent future contracts in case of default can discourage strategic defaults (Stiglitz and Weiss, 1983). Diamond (1991) has also found that borrowers with a better reputation (e.g. from successful uses) require less monitoring.

These theories are all useful to explain the motivations behind the pay-on-demand lending model. Given the use case of pay-on-demand, it is likely that the lenders are lending to a borrower with a relatively high default rate (see section 5.2.1 for more information). Similar to the lenders operating under asymmetric information in the theories of credit rationing, pay-on-demand providers are lending to borrowers who know more about their capability to repay the debt, and who may not repay the debt even if they have the ability to repay. This leads to an environment of information asymmetry, causing adverse selection and moral hazards. Individuals who want to use pay-on-demand may be those to whom pay-on-demand providers do not want to lend. Evidence for information asymmetry is that *MyPayNow* rejects over 60% of their applicants (Jeong, 2021). This is analogous to other many other unsecured lendings, such as credit cards. For example, Ausubel (1999) documented empirical evidence of adverse selection, that respondents to credit card solicitations are substantially riskier than non-respondents. Therefore, the core of the operations of pay-on-demand is to design their loan terms and conditions so that information asymmetry is reduced.

Interest rate is not a useful device to screen out debtors, both due to information asymmetry and the regulatory pressure from the NCCP Act 2009, which prevents pay-on-demand from offering different levels of interest rates based on the risks of the customers. Increasing interest rates or offering inferior terms lead to customers pools of much higher credit risk level (Ausubel, 1999). Although screening based on credit scores can substantially reduce the default rate, doing so may reduce the total volume of credit and increases the cost to service each loan, so the profitability is worsened.

Since pay-on-demand's use case targets those users without a credit score, it has adopted non-traditional methods to choose whom they lend to. Consistent with Stiglitz (1975)'s theory of screening, pay-on-demand providers need to learn more about the intrinsic credit quality of the borrowers. This takes place in the advertising, the initial screening stage of the pay-on-demand application, and throughout the uses of pay-on-demand. In advertising, the lenders sponsor specific advertising programs whose targeted viewers are consistent with the use case of pay-on-demand. For example, *MyPayNow* sponsors Gold Coast Titans, a professional rugby league football club. The demographics of the viewers of NRL and the users of pay-on-demand are similar, leaning towards males under 30 years old, and these people are a significant part of the Australian casual workforce who earn lumpy wages. Consistent with Cao and Gruca (2005), this alignment between targeted users and viewers of advertisements improves loan profitability.

During the application phase, as the users submit their identification, bank statement and their pay-cheques, this information will be processed by the proprietary algorithms developed by the pay-on-demand providers, which assess the credit risks of the applicants using transaction scoring. Based on the algorithm, applicants who are classified as bad will be rejected, and the rest of the applications will be accepted. All applicants that pass through the initial screening stage will be eligible to use pay-on-demand.

Finally, the borrowers could also obtain more favourable contract terms by signalling their credit worthiness through successful repeated uses. Demonstrating a history of successful uses with a pay-on-demand provider will gradually increase the maximum wages that the providers may advance, as successful uses are signals of good credit qualities (Boot and Thakor, 1994).

The moral hazard problem is mitigated by incentivising the borrowers to repay their advanced wages, as demonstrating a good history of repayment will increase the maximum accessible wage. No further credit will be granted until the outstanding balance is repaid, since the termination of future contingent contracts will also reduce moral hazard (Stiglitz and Weiss, 1983). To control for strategic default, an action in which borrowers refuse to repay their debt obligation despite having sufficient liquidity, pay-on-demand mandates direct debit and only allows borrowers to advance on earned wages, effectively always using the next pay cheque as collateral. These three terms lower the credit risks of pay-on-demand by addressing the incentive problem in the credit market.

3.2 Pay-on-demand

Baker and Kumar (2018) compared the interest rate of pay-on-demand to other market alternatives of a similar credit loss. Although the probability of default for the users of pay-on-demand translates to a FICO (credit) score range of 480-500, the APR from pay-on-demand is lower than the obtainable interest rate of someone with a credit score of 700. Therefore, he asserted that pay-on-demand is welfare-improving by saving interest costs, since individuals with such credit scores typically need to rely on high APR loans such as auto title loans or payday loans with an APR of over 199%. Additionally, users of this given credit risk interval (480-500) are often unbanked, and so pay-on-demand may improve credit access. Similarly in Australia, the credit loss rate from Beforepay's

FY21 financial statement is 24.56%. Thus, borrowers within this group would also be considered 'subprime,' with limited credit access.

Donner and Siciliano (2022) documented other direct and indirect costs that using pay-on-demand could save, including the damage to credit reputation due to strategic default on credit cards (Liberman, 2016) and short-sighted career choices such as gig work (e.g. delivering for Ubereats).

The main reason why pay-on-demand is able to maintain as a going concern while charging such a low interest is the salary link (Baker and Kumar, 2018). Pay-on-demand providers (e.g. *Beforepay* and *MyPayNow*) are able to estimate the time that their users are paid their wages, thereby debiting the account directly at the time of pay. Assuming that the pay-on-demand providers are able to correctly estimate the time that the borrowers are paid, the salary link will ensure that (1) the default rate will remain low, (2) the lenders have an information advantage and (3) have the most prioritised claim on the borrower's debt. Together, these three advantages ensure that although pay-on-demand is non-secured debt, the credit loss will be low, thus enabling the lenders to make profits at a low interest rate.

Similarly, Hawkins (2021) made a comprehensive comparison between payday loans and pay-on-demand, highlighting the superiority of pay-on-demand and predicting that pay-on-demand will replace a large proportion of the payday loan market. Due to the salary link, lenders may have superior access to information, which helps screen borrowers better, lower loan losses and lower transaction costs. These results are complementary to the results of Berg et al. (2021), who found that Fintech lenders could improve screening to a certain extent through non-traditional data sources. The fast processing time of the Fintech lenders enables them to adjust more quickly to a change in credit demand, which translates to a saving in operating expenses. Evidently, during the pandemic, measurements such as social distancing and working from home have reduced the supply of mortgages, which involve time-consuming and complex underwriting, but at the same time Fintech lenders gained market share (Fuster et al., 2019, 2021). These cost reductions could ultimately benefit the borrowers and improve their financial situation, as the interest that the borrowers need to pay will be lower.

However, Hawkins (2021) also argued that the realisation of the benefits outlined by Baker and Kumar (2018) is conditional upon the existence of effective regulation, such as ensuring the terms of pay-on-demand are not predatory and assuring that pay-on-demand is a non-recourse loan. The Australian media (e.g., the AFR) has called for more stringent regulation on pay-on-demand, but so far pay-on-demand has not yet been regulated as a credit. Other risks of the product highlighted by Hawkins (2021) include the aggressive collection mechanism eliminating the option to strategically default, which Gerardi et al. (2018) have shown to be a valuable method for managing liquidity and the access to credit leading to temptation or impulsive purchases.

Using individual-level transaction data provided by a provider (*Minu*) of earned wage access in Mexico, Murillo et al. (2022) provided empirical evidence for how earned wage access is used. Males, younger and individuals who joined the firm for a longer time are more likely to use Minu. On the positive side, the authors found that pay-on-demand helps act as liquidity insurance against a revenue-expenditure mismatch and cash shortfalls. However, on the negative side, similar to claims that payday loans ensconce users into a debt spiral, the frequent users of Minu tend to increase their advances over time, and the withdrawal tends to happen earlier in their pay cycle. Additionally, similar to the present bias issue with payday loan use (Zaki, 2016), Murillo et al. (2022) found a subset of users that do not use Minu for financial constraints.

Baker and Kumar (2018); Hawkins (2021) and Donner and Siciliano (2022) all provided useful insights into why pay-on-demand is beneficial or harmful to the borrowers, but these results are based on a summary of existing theories, and no empirical evidence is provided. As Donner and Siciliano (2022) asserted, the question of whether pay-on-demand improves or worsens credit access ultimately depends on how pay-on-demand is used and who uses pay-on-demand. Pay-on-demand is helpful to the extent that it smooths income and bridges the liquidity gap caused by revenue and expenditure mismatch, but is also harmful if used incorrectly to fund temptation purchases, so ultimately the question of whether pay-on-demand improves welfare is an empirical question that needs to be tested using rigorous statistical technique (Baker and Kumar, 2018).

Although Murillo et al. (2022) provided empirical evidence through analysing transaction data, Minu's earned wage access differs significantly from *MyPayNow* and *BeforePay*. Firstly, Minu is based on a direct-to-business model, whereas the pay-on-demand providers in Australia are based on a direct-to-customer model. Hawkins (2021) asserted that the latter model gives the customer the option to withdraw their wages before the deduction, effectively giving customers greater control over their wages. However, this option is at the expense of an overdraft or a potential dishonour fee, both of which are expensive in Australia. Secondly, Minu charges a fixed fee of 39 pesos (2.76 AUD), whereas pay-on-demand in Australia charges a 5% "transaction fee." Finally, pay-on-demand in Australia is often associated with a hidden cost from unsuccessful payments. Therefore, we fill the lack of empirical evidence in Australia by examining a unique Australian dataset supplied by the Commonwealth Bank of Australia (CBA).

3.3 Pay-on-demand and payday lending

Due to the qualitative similarities between payday loans and pay-on-demand, the impact of using payday loans will be similar to the impact of using pay-on-demand. Both products have similar use cases. Both pay-on-demand and payday loans fall into the category of SACC, and both provide similar types of liquidity by financing the employees between each payday.

In addition to having a similar use case, pay-on-demand may be more appealing to users than payday loans. Levy and Sledge (2012) documented the reasons why borrowers may choose payday loans over other products: they are not qualified or already over the limit on credit cards and other instruments, they regard traditional instruments as too expensive, and they think the traditional instruments are less convenient. Pay-on-demand products fill each of these gaps. Because pay-on-demand providers do not perform credit checks, it enables unbanked or low credit-score customers to access credit. The cost to access – the flat 5% transaction fee – is considerably lower than the relative costs for a payday loan. As a Fintech product, the approval process of pay-on-demand is very quick as the providers use algorithms to calculate loan sizes, meaning that pay-on-demand is likely to be regarded as more convenient by many users.

Extant literature has discussed payday loans in terms of the welfare impact of payday loans. However, existing research shows mixed results on whether payday loans improve or deteriorate the welfare of the users. Zinman (2010) and Morse (2011) found supporting evidence for the beneficial view, Melzer (2011), Cuffe and Gibbs (2017), Zaki (2016) and Skiba and Tobacman (2019) found supporting evidence for the harmful view, and Morgan et al. (2012) has found mixed evidence for both views.

The fundamental argument supporting the view that payday loans improve welfare is that payday loans provide valuable liquidity, without which the users are forced to use more harmful loans or live without essentials. Using a propensity score matching the differences-in-differences method, Zinman (2010) tested the impact of Oregon reform, an action that placed a price cap on the fees charged by payday loans and forced many payday lenders out of business. Zinman then found that, in Oregon, unemployment and pessimistic perceptions of the future financial situations increased more than in Washington. The reduction in the credit supply of payday loans limited the borrowers' ability to access credit, thus their financial condition deteriorated. In a similar vein, using a differences-in-differences (DID) approach, Morse (2011) finds that access to payday lending reduces foreclosures during natural disasters (as borrowers are able to avoid significant delinquency costs caused by a lack of short-term liquidity), implying a positive effect of payday lending. Furthermore, Morgan et al. (2012) found that the number of returned checks and bank overdraft income is lower when the payday credit supply expands. Hence, at least a proportion of users use payday loans as a substitute for bank overdrafts, which are considerably more expensive. Analogously, if pay-on-demand is used for income smoothing, it may also be a useful tool for reducing interest expenses, hence improving financial health for the users. Additionally, as Gelman et al. (2014) document that consumers with the lowest liquidity experience the strongest payday effect, if pay-on-demand is primarily used for smoothing income, the improvement will be the strongest among the low liquidity groups.

The opponents of payday lending argue that payday lending overall destroys welfare, because (1) the costs are too high and (2) because the users misuse their access to credit. Consistent with the criticism that payday loans are too expensive, Skiba and Tobacman (2019) find that payday loan applicants who are barely approved (just crossing the credit score threshold) for their first payday loans are significantly more likely to file for bankruptcy than those who are barely rejected. Skiba and Tobacman (2019) thus argue there are negative welfare effects from accessing payday loans, most likely because payday loans worsen borrowers' cash flow positions due to the extremely high costs. Consistent with the misuse argument, both Melzer (2011) and Cuffe and Gibbs (2017) find evidence that payday loans are not utilised for essential purchases. Melzer (2011) shows that access to payday loans hinders the users' ability to pay for the essentials and in some cases caused them to delay needed medical services. Cuffe and Gibbs (2017) showed that US state laws that restricted access to payday ending led to a reduction in alcohol purchases, and the sharpest decreases are for the stores that are located closest to a payday lending store.

Zaki (2016) employs the restrictions of payday lending of the Military Lending Act (MLA) as a natural experiment, and finds that payday loans alleviate liquidity constraints by smoothing food consumption, but at the same time access to payday loan increases total alcohol consumption. Since the interest costs of payday loans are extremely high, only individuals with extremely high utility to immediate consumption will use payday loans to purchase non-essential commodities. Therefore she concludes that some proportion of payday borrowers are present-biased. Together, these are evidence that at least some payday borrowers have inappropriately used the proceeds from payday loans, implying a negative welfare impact of access to payday loans.

Even worse, payday lenders may exploit these behavioural biases to nudge the borrowers to borrow more. Therefore, a similar effect may exist also for pay-on-demand users. Access to pay-on-demand increases the frequency of income, which is shown to increase discretionary spending because it creates a perception of being wealthier (De La Rosa and Tully, 2020). Aguiar and Hurst (2013) has shown that without access to credit, borrowers may decide to save the money for precautionary reasons; hence access to pay-on-demand may also adversely impact the borrowers. Hawkins (2021) also highlighted temptation and over-consumption as major risks of the product. The lack of effective regulation of disclosure for pay-on-demand may further induce customers to over-borrow, similar to the case of over-borrowing with payday loans (Bertrand and Morse, 2011). Hence, if pay-on-demand is used to fund excessive consumption, access to credit through pay-on-demand may also worsen the credit risks.

A summary of the payday lending literature found two main reasons why payday lending could be harmful. First, the high interest and late fees charged are simply too expensive for the customers, and the benefit of liquidity does not exceed the high financing costs. Second, payday lending instils a psychological impact on the borrowers, causing them to misspend their money on non-essentials or become short-sighted. One way to settle the debate of whether payday loan reinforces welfare is to study the effects listed above separately. Since the main difference between payday loans and pay-on-demand is that pay-on-demand charges no late fees, this provides a natural experiment setup that enables us the test each of the effects separately. Hence, this thesis contributes to the payday lending literature in a different context by answering the question: how much less harmful could payday loans be if the high fees are removed? The thesis also contributes to the scarce literature on payday lending based in a non-US setting.

Another strand of payday lending literature investigates whether payday loans should be replaced. Unlike the question of welfare effect, there is a consensus that a similar, but the less costly product can make the borrowers better off, because payday loans' high interest may not be reflective of their cost to provide credit (e.g. (Morse, 2011), (Ossip, 2020)). This opinion is even supported by many scholars who found evidence that payday loans improve social welfare. Furthermore, Edmiston (2011) argued that directly eliminating payday loans without providing a viable alternative could also hurt consumer welfare, because forced switching forces these users to use more welfare-damaging products like pawnshop loans. Despite the importance of replacing payday loans, however, there is a lack of critique of a viable alternative for payday lending. This thesis aims to partially fill this gap by examining the impact of pay-on-demand (earned wages access), a potential candidate for replacing payday loans.

3.4 Pay-on-demand and Buy Now, Pay Later

The literature on BNPL is also useful to this thesis, as both BNPL and pay-on-demand are Fintech lending products that are excluded from the NCCP Act 2009. Neither products need to perform a credit check, thereby attracting similar groups of customers. Pay-on-demand users are likely to use pay-on-demand similarly to how BNPL users use BNPL.

Extant literature has documented who uses pay-on-demand. BNPL attracts subprime borrowers who are more financially vulnerable and financially illiterate. Boshoff et al. (2022) found that users of multiple BNPL services are much riskier and credit constrained. Guttman-Kenney et al. (2022) found BNPL usage is significantly higher in deprived areas of England, and a significant proportion of customers charge their BNPL to credit cards, both warning flags of BNPL users being financially constrained. Woolard (2021) has found evidence that the advertisements of BNPL may take advantage of consumers' behavioural biases, including present bias, availability bias and confirmation bias. Although the providers of BNPL claim to benefit[3] customers by smoothing expenses, Gerrans et al. (2022) has found that the realisation of such benefit is conditional on adequate financial literacy. Hence, users of pay-on-demand should also be riskier than non-users, and they should have a lower level of financial literacy.

BNPL is associated with misuse, and evidence suggests using BNPL may be welfare-

[3]For example, AfterPay claims "to help customers get what they need without existing in an ongoing state of debt." See `https://www.afterpay.com/en-AU/how-it-works`

destroying. Australian Securities and Investment Commission (2020) has found that 20% of BNPL users had to cut back essentials, and 15% of BNPL users had to take out an additional loan to meet their BNPL obligations. Using a survey of 109 females aged 18 - 25, Ah Fook and McNeill (2020) has identified that being a BNPL user is associated with present and future impulsive purchasing in an online environment. Unsuccessful uses with pay-on-demand, therefore, may also be welfare-destroying.

4 Hypothesis Development

4.1 Who uses pay-on-demand?

As pay-on-demand is a newly introduced product to the Australian market, our first aim is to examine the clientele of pay-on-demand products. This question is important because whether pay-on-demand alleviates financial constraints depends on who uses them (Hawkins, 2021; Donner and Siciliano, 2022).

The first hypothesis is related to the age and gender characteristics of the users. Given the Fintech nature of the product, and its use case to fulfil the liquidity gap of casual workers, the product should mainly target young people who are sophisticated with technology, and who earn a lumpy wage. People who work on shifts are also younger than workers who do not. The marketing strategies of *MyPayNow* and *BeforePay* directly appeal to male viewers, so males are more exposed to the pay-on-demand.

Hypothesis 1 (H1): *Younger and male workers are more likely to use pay-on-demand.*

Gelman et al. (2014) have found that people from lower income groups have stronger payday effects, needing short-term liquidity more often. Therefore, people with lower income receive more utility from accessing their wages early.

The concentration of pay-on-demand usage is likely to be higher in lower socioeconomic areas because of stronger liquidity constraints and lower financial literacy. Since people with lower financial literacy perceive more benefit from using BNPL (Boshoff et al., 2022), a similar effect may exist for pay-on-demand applicants. People from lower socioeconomic areas may also use pay-on-demand as they perceive greater benefit from it.

Hypothesis 2 (H2): *People who earn lower income and live in lower socioeconomic areas are more prone to use pay-on-demand than those who earn higher income and reside in higher socioeconomic areas.*

Whether a user has access to other forms of finance is also likely to influence the decision to use pay-on-demand. A user with access to a cheaper (or more convenient) form of finance would be unlikely to use pay-on-demand. Users with higher credit risk will lack alternative access to credit, so they will be more likely to use pay-on-demand. This is the case with BNPL (Boshoff et al., 2022). In addition, it is not uncommon for credit card users to access payday loans, despite payday loans being much more expensive than credit cards (Agarwal et al., 2009). An explanation is that credit card users who have a high utilisation rates may need other loans to balance their liquidity and avoid default (revolving credits). Otherwise, credit defaults will damage their credit score, possibly leading to a loss of access to further finance from credit cards. Thus, we predict a positive correlation between credit card utilisation rate and the probability of using pay-on-demand.

Hypothesis 3 (H3): *Holding all else constant, the probability of using pay-on-demand is higher for people with higher credit risk. People with higher credit card utilisation rate are more likely to use pay-on-demand.*

4.2 Who pays unpaid payment fees?

If borrowers cannot repay their debt, adverse outcomes may happen to both the borrowers and the lenders (Boshoff et al., 2022). For pay-on-demand users, unsuccessful uses are often associated with extra unpaid payment fees. Every time the users of pay-on-demand fail a repayment (due to insufficient balance in the bank account), a $5 dishonour fee is imposed. As the providers usually attempt to deduct the wages multiple times in case the first deduction fails, this amount will compound to a significant cost to use the product.

Since unpaid payment fees are charged when the cash balance is low, users with less regular income and less saving will be at the greater risk of paying unpaid payment fees. Meier and Sprenger (2015) also found that people with lower income are also more present-biased, so they should also use pay-on-demand more impulsively and less successfully. Hence, I hypothesise that individuals who have a constant salary, earn more income, have more savings are less likely to dishonour their pay-on-demand debt.

Hypothesis 4 (H4): *Users with a lower saving balance, who do not earn a constant salary and earn less total income are less likely to be successful pay-on-demand users.*

Hibbeln et al. (2020) found information synergies in consumer credit. The activities in one product are predictive of the default risk of the other accounts and vice versa. Credit card information should therefore be predictive for pay-on-demand usage. On the other hand, Nakamura and Roszbach (2018) examined banks' private information related to an external credit rating. Consequently, they found bank private information in the form of banks' private ratings on borrowers can be predictive of future borrowers' default, and the predictability is greater for loans of smaller sizes. Given the small size of pay-on-demand loans, banks' private ratings may have very strong predictive powers. Hence, I hypothesise that individuals with credit card pay are more likely to be successful users. However, less successful credit card users (users with a high utilisation rate and past delinquency records) are less likely to be successful with pay-on-demand. Users with a hardship arrangement are more likely to fail to use pay-on-demand successfully. Customers labelled as safer by the banks are also less risky to the pay-on-demand providers.

Hypothesis 5 (H5): *Credit card users are less likely to default on pay-on-demand. However, credit card users with a high utilisation rate and past delinquency records are riskier to pay-on-demand providers. Customers that have a hardship arrangement are more likely to default on pay-on-demand. Safer bank customers are safer pay-on-demand customers.*

On one side, pay-on-demand targets less liquid credit users by providing them with liquidity. Nonetheless, people with lower liquidity are more likely to run out of cash, thus at greater risks of being penalised an unpaid payment fee. This potential conflict may limit the extent to which pay-on-demand may improve financial resilience for the users.

4.3 Who uses pay-on-demand more?

The final question answered by this research is related to the intensive margin to which users use pay-on-demand. This question is important because of claims that pay-on-demand could force people into a debt spiral, like payday loans. If the most repeated and heaviest users of pay-on-demand are those facing financial problems, it is a warning sign that pay-on-demand exacerbate financial stress. Here, I consider both the frequency and the amount of wage that users borrow from pay-on-demand.

Because pay-on-demand providers only perform a bank statement analysis and not a credit check, I only make a prediction on the coefficients of the variables that pay-on-demand lenders have access to, including *Socioeconomic Decile, Deposit Savings Balance, Income, Salary Type* and *CC Flag*. Addresses are submitted together with the bank statement upon application for pay-on-demand, which could be used to infer postcode-level information, such as socioeconomic status. Similarly, deposit savings balances can be directly observed from an applicant's bank statements. Income and salary type can be identified using the lender's proprietary algorithm, which identifies specific transactions that correspond to the receipt of wages. In a similar vein, the lenders may be able to infer the credit card holdings of an applicant through the analysis of the bank statement.

Users from higher socioeconomic deciles, always depositing their salary into accounts, and those having higher savings balances will be assessed as safer customers due to stronger financial resilience. Having a credit card may be assessed as a signal for lower credit risk because the user must have had sufficient credit quality to obtain a credit card at one stage (even if not presently). Users with relatively strong financial positions will have more access to pay-on-demand, despite requiring less frequent access to the product. Since *MyPayNow* and *BeforePay* only allow users to access their expected wages in advance, users with lower wages will be extended a smaller credit line. Hence, I hypothesise that users who are from richer socioeconomic areas, always earning a salary, earning a higher salary, those who have more savings, and those with a credit card will borrow a greater amount from pay-on-demand.

Hypothesis 6 (H6): *Users from higher socioeconomic deciles, users always earning a salary, users earning more salary, users with more savings and users with a credit card will borrow a greater amount from pay-on-demand.*

Two conflicting forces are likely to affect the frequency of use of pay-on-demand. Users who are less financially resilient have greater and more frequent liquidity needs, driving them to use pay-on-demand more frequently. Australian Securities and Investment Commission (2020) and Boshoff et al. (2022) have found that repeated users of BNPL and users of multiple BNPL product are more likely to miss payments and default on their credit cards, and these groups usually have a less stable income and limited savings. Levy and Sledge (2012) revealed cash shortages to be strongly correlated with repeated uses of payday loans. Nonetheless, to be able to take out multiple wage advancements, users need to use the product successfully several times, which is more difficult for users with less aggregate liquidity (see Hypothesis 4 and 5).

Therefore, more frequent pay-on-demand usage is an empirical question that needs to be tested. My hypothesis is that more frequent users of pay-on-demand are less financially resilient, while having more frequent liquidity needs. Such individuals are likely to be more credit constrained and have less reliable income sources, and be from lower socioeconomic areas. Thus we have

Hypothesis 7 (H7): *Users from lower socioeconomic deciles, users who do not always earn a salary, users with lower income, users with lower savings and users without credit card will borrow more frequently from pay-on-demand.*

5 Data

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

I explore the transaction data of the debit account of pay-on-demand users in 2022 March, supplied by the Commonwealth Bank of Australia[4]. Only a debit account is chosen because pay-on-demand providers could not directly debit a credit account; hence only information from the debit account is useful. 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`. A debit to the customer's account reduces the total balance of the customers, representing a cash outflow (repayment), and a credit to the customer's account increases the total balance of the customers, representing a cash inflow (a loan). 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 from **CommScore**, using both unique account-level identifiers and customer-level identifiers. **CommScore** 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 **CommScore** database. The second dataset 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.

[4]In previous part of the thesis, I have used transaction data from 2020 August to 2022 January perform analysis on how pay-on-demand is used by its users. Although the time series data enables more tests to be performed and more rigorous econometric techniques to be used, the demographic, socioeconomic and credit information on the individual users is only available for one month. Therefore, we are only able to perform test on a cross-sectional dataset instead of a panel.

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. I 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.

The unique feature of the dataset employed by this study is the availability of individual-level data. Prior studies of other SACC (e.g., payday loans) typically rely on zip-code/county level data (i.e., Morse (2011)). However, since we are only able to obtain user data from CBA, customers of pay-on-demand that do not use CBA are consequently excluded from the sample. This does represent a limitation of the studies. Nonetheless, given that CBA serves 15.9 million [5] of 19.5 million bank customers [6] in Australia, we believe the impact of excluding non-CBA customers would not materially affect the robustness of the results.

The remainder of the section will present several interesting aspects of the pay-on-demand users. By comparing the characteristics of pay-on-demand users to that of an average Australian, I have identified certain traits that make someone more likely to use pay-on-demand. The results here are consistent with hypothesis 1 to 3. We found evidence that younger males from poorer socioeconomic deciles with less income are more likely to use pay-on-demand. Users of pay-on-demand are also significantly riskier than non-users, and much more likely to have a highly utilised credit card if they have one.

5.2 Summary Statistics

5.2.1 Demographic and socioeconomic characteristics

Table 2 reports the summary statistics of the key user characteristics. Figure 6 presents

[5] Source: `https://www.commbank.com.au/about-us/our-company.html` "*today, we've grown to a business that serves 15.9 million customers*"

[6] Source:`https://www.ausbanking.org.au/insight/banking-by-the-numbers/`

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
Credit Card Pre-Approval Score	-48	165.81	-156	-38	75
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 10. 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.

the distribution of key demographic and socioeconomic characteristics that are hypothesised to be useful for predicting pay-on-demand usage. Firstly, Panel A shows the age composition of pay-on-demand users. The product is used predominantly by the younger population, as the majority of users are less than 30 years old. Since the casual work forces are significantly younger than the non-casual workforce, the young age of the users suggest that the actual use of the product may be consistent with its use case, which is to bridge the liquidity gap of people earning volatile wages. Viewers of the national rugby league are of a similar age composition, and the similarity is likely explained by the product's marketing strategies.

The majority of pay-on-demand users being young is also analogous to users of other Fintech lending products, such as BNPL (Berg et al., 2021; Australian Securities and Investment Commission, 2020), because the younger generations are more sophisticated with technology.

Furthermore, in most age brackets, there are more males using the product compared to females. Together, the age and gender characteristics are consistent with the demographic of pay-on-demand in Mexico (Murillo et al., 2022). In contrast, BNPL, another Fintech lending product, is used predominantly by females. Such a difference is likely a result of different marketing strategies that aim to attract difference audiences.

Panel B shows a comparison between pay-on-demand users and the average population, in terms of the socioeconomic decile of their addresses. Decile 1 refers to the poorest regions, whereas decile 10 corresponds to the most affluent zip codes. The number of pay-on-demand users does not vary significantly between each decile, because the number of people living in each decile is different, and this population difference may offset the impact of people from poorer being more prone to use pay-on-demand. Decile 4-6 has on average more people residing there. Hence, we account for this difference by dividing the number of pay-on-demand users by the average population of the zip codes of each decile, and the user-population ratio shows that on average people from poorer deciles are more likely to use pay-on-demand.

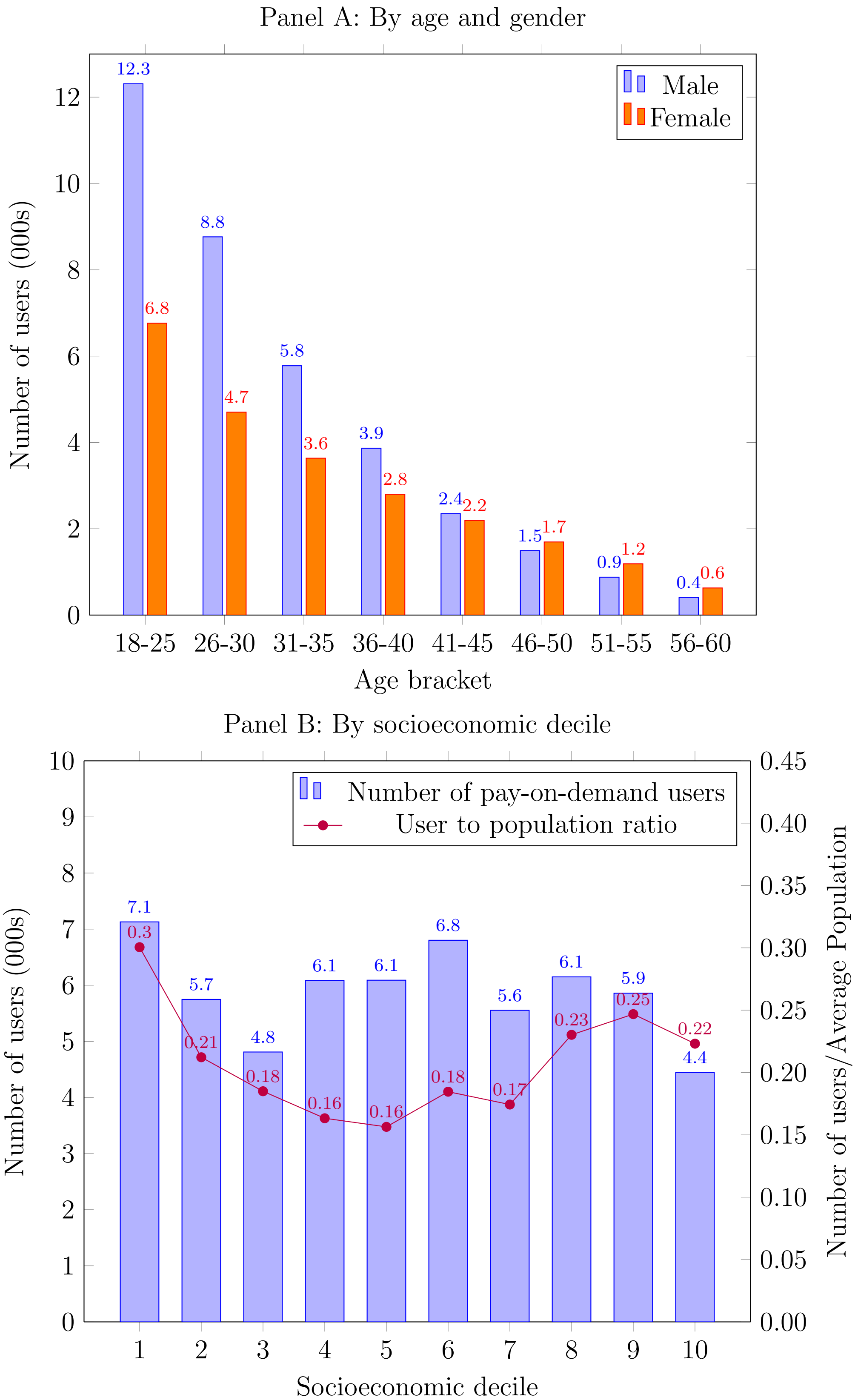


Figure 6: Demographic and socioeconomic characteristics

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 5. Panel A plots the number of users in each gender-age group. Panel B presents the number of users in each socioeconomic decile.

As displayed in the summary statistics table (Table 2), not all users have a constant or stable salary, which is inconsistent with the eligibility criteria of pay-on-demand. 31.1% of the users never received a salary, and 9.1% of the users' salaries ceased but continued to use the product. Over 40% of the users of pay-on-demand should not be using pay-on-demand, suggesting a flaw in the transaction scoring algorithm employed the providers. The lenders are not notified about the changes in the employment status.

The median income for the pay-on-demand users is only $31,000, which is considerably lower than the median income of Australian of $62,868 per year (Australian Bureau of Statistics, 2022a). This median may be distorted because over 25% of the pay-on-demand users are not earning any income at all, as per CBA's algorithm. Hence, in Figure 7, we plot the distribution of annual estimated income of pay-on-demand users, for those whose income exceed $20,000. Still, the majority of the population earned less than $60,000 per year, meaning pay-on-demand is predominantly accessed by the lower-income group. We also plotted the average loan-to-income ratio in the same graph, to investigate how heavily people from different income levels rely on pay-on-demand. When expressed as a ratio of loan to income, people with lower income tend to advance more. This trend is consistent with Gelman et al. (2014), who found that people with less liquidity tend to experience stronger payday effect. Hence, they need more liquidity to bridge the cash flow mismatch, advancing more of their wages.

Consistent with the use case, pay-on-demand aims to fulfill the liquidity gap between each payday by enabling the users to access their pay-cheque before the time of pay. The stronger the payday effect, the more liquidity that the users need, so more advancements of wages are made. Evidently, the Fintech nature of the product has disproportionately attracted a group of young users who are sophisticated with technology and are also working on shifts receiving lumpy wages. However, I have also identified a huge subset of active users that should not be using pay-on-demand, as their salary has ceased or they have never received a salary at all. In subsequent sections, I have shown that these users are also paying a significant amount of unpaid payment fees, which deteriorated their

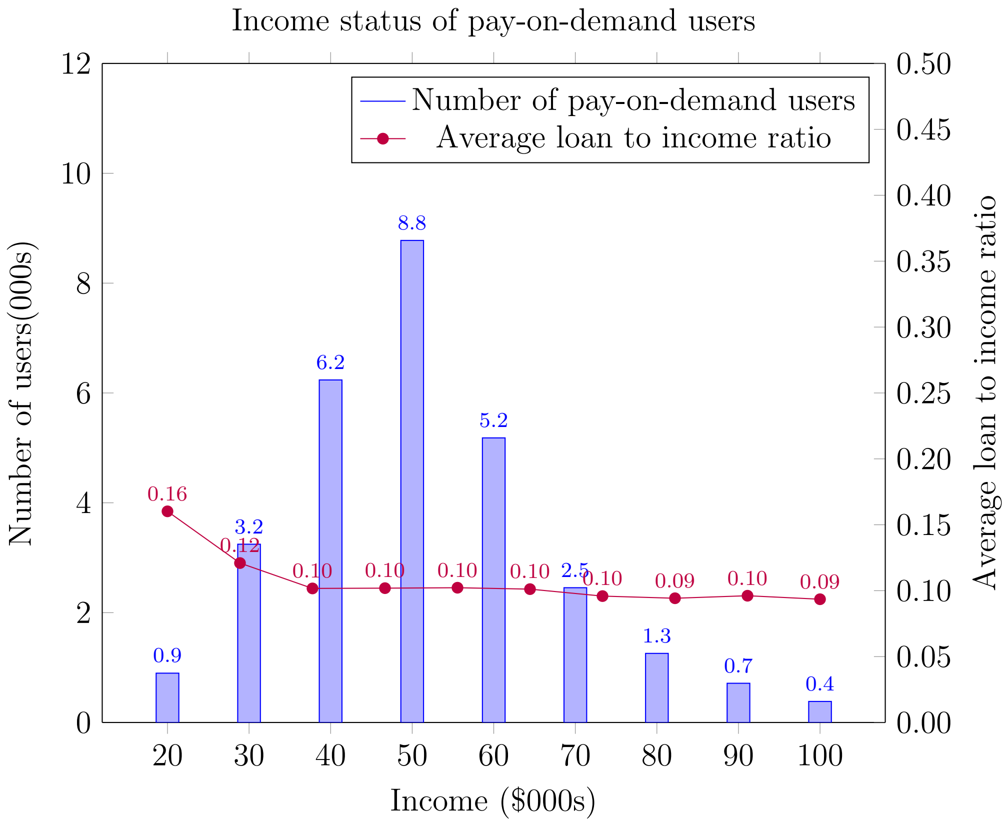


Figure 7: Employment and income status

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.

financial status.

5.2.2 Other product co-holdings

Only 17.1% of the pay-on-demand users have a credit card, which is significantly less than the proportion of Australian population and BNPL users who have a credit card. In comparison, Cooke (2022) discovered that there are 13.7 million credit card users in Australia out of the total 25.69 million population, and Boshoff et al. (2022) have found that 30.5% of the BNPL users have a credit card. There are two factors contributing to the low presence of credit cards among the pay-on-demand users. Since pay-on-demand performs no credit check, it has attracted users who are unable to obtain credit otherwise due to a damaged credit reputation. Second, the Fintech nature of pay-on-demand means it is skewed towards the young users, who are less likely to use a credit card due to risk aversions and poor credit rating (Lowrey, 2013).

In comparison, the proportion of users that have a highly utilised credit card (utilisation rate $> 95\%$) is 12.5%. This equates to 73.1% of the credit card holders having over 95% utilisation rate. In contrast, only 38% to 43% of the BNPL credit users use over 90% of their credit line on their credit card (Australian Securities and Investment Commission, 2020).

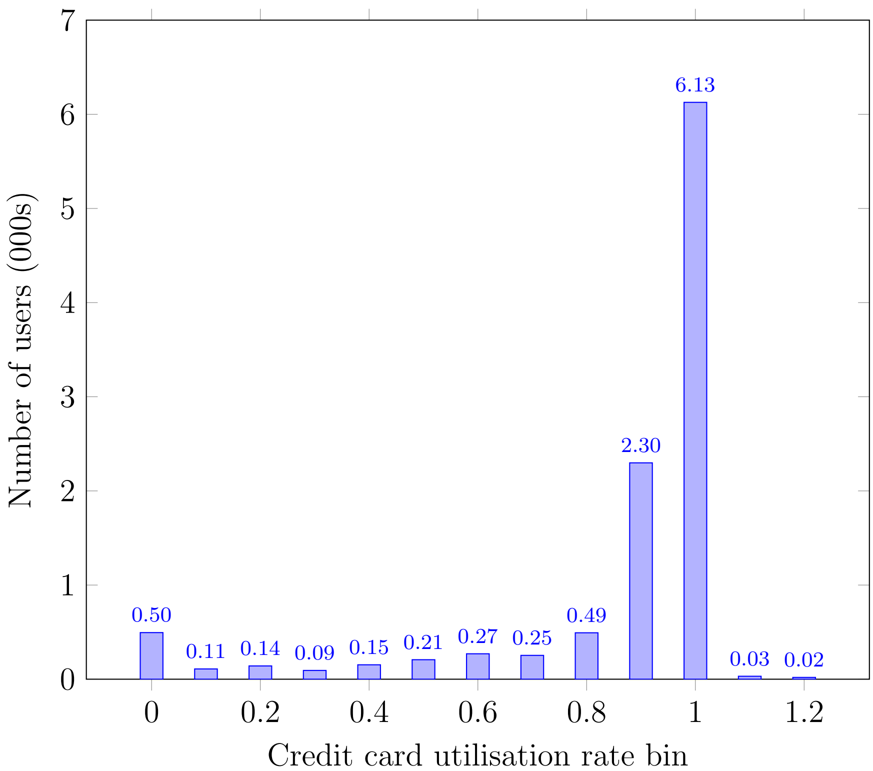


Figure 8: Credit card utilisation

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

Figure 8 plots the number pay-on-demand customers in each credit card utilisation bin. Most 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. There is also evidence that pay-on-demand users are cross-subsidising their credit card with pay-on-demand. since pay-on-demand users that have a credit card also tend to rely more heavily on pay-on-demand. Compared to non-credit-card users, pay-on-demand users on average advance \$80.51 per month, and advance a slightly higher proportion of their annual income (10.97% vs 10.30%).

Apart from having a higher utilisation rate, pay-on-demand credit users are also more likely to have a past delinquency record compared to average users. 12.4% of the total users had at least one past delinquency record, meaning 72.51% of the credit card users of the pay-on-demand sample has defaulted on their credit card at least once. 31.58% of the pay-on-demand credit card users have defaulted more than once. In contrast, in the sample of BNPL credit card users examined by Boshoff et al. (2022), only 23.28% of the credit card users had a past delinquency record.

5.2.3 Credit risk variables

Firstly, we examine the credit risks in terms of the customers' risk grades, which is a benchmark that CBA has produced to evaluate the risks of the customers in their lending decision. A higher risk grade means the customer is riskier, and a lower risk grade implies a safer customer. Risk grade 0 is assigned to ungraded customers who recently joined the bank, and risk grade 5 is assigned to customers who are difficult to score. In Figure 9, I plotted the number of customers in each risk grades, and found that pay-on-demand users are skewed towards users from a higher risk grades, meaning these bank customers are much riskier and much more difficult to score.

Since the majority of pay-on-demand users receive a grade of 3 to 5, they are significantly riskier than the average bank customers, as the median grade is between 2 and 3. In contrast, Boshoff et al. (2022) examined the BNPL users using the same customer risk grade variable from CBA, and found that the 73% of BNPL users fall into risk grade 1 and 2. There are two reasons why pay-on-demand users are on average much riskier. Firstly, the use case of pay-on-demand has attracted a group of risky users who lack alternative access to credit due to high credit risks, and are earning more volatile and lower

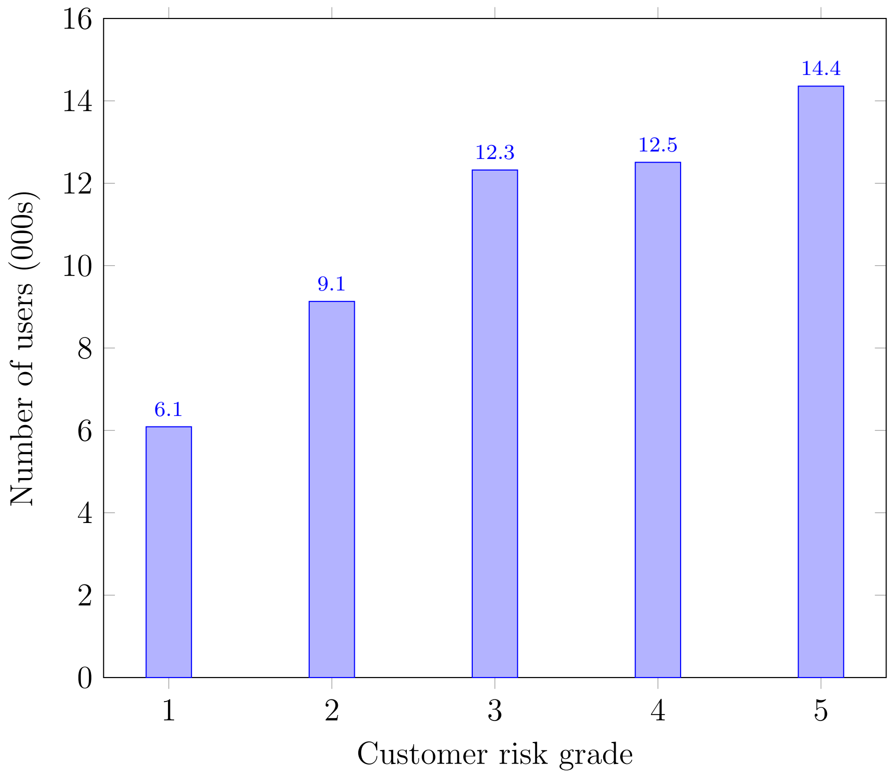


Figure 9: Distribution of customers by risk grade

Notes: This figure presents information on the number of the users in each customer risk grade. Grade 4 is assigned to the most risky customers, and grade 1 is given to the safest customers. Grade 0 is unscored, and grade 5 is for bank customers who are difficult to score.

income. These factors are picked by the scoring algorithm so a lower score is produced. Second, the unsuccessful use of pay-on-demand leads to unpaid payment fees, which will also feed into the scoring algorithm and result in a poorer rating. The average credit card pre-approval score is -48, a score that is below the minimum approval threshold for a credit card. Together, the high credit risk nature of the pay-on-demand users may also imply that pay-on-demand users lack access to alternative sources of finance. Those with a credit card have already maxed out the credit line. Users without a credit card have have difficulty obtaining one due to their low credit card pre-approval score. Thus, the credit constrained groups are a valuable user base to pay-on-demand, which creates more incentive for pay-on-demand not to perform a credit check. Suppose the users use it successfully, pay-on-demand represents a valuable source of credit to its users.

5.2.4 Pay-on-demand usage pattern

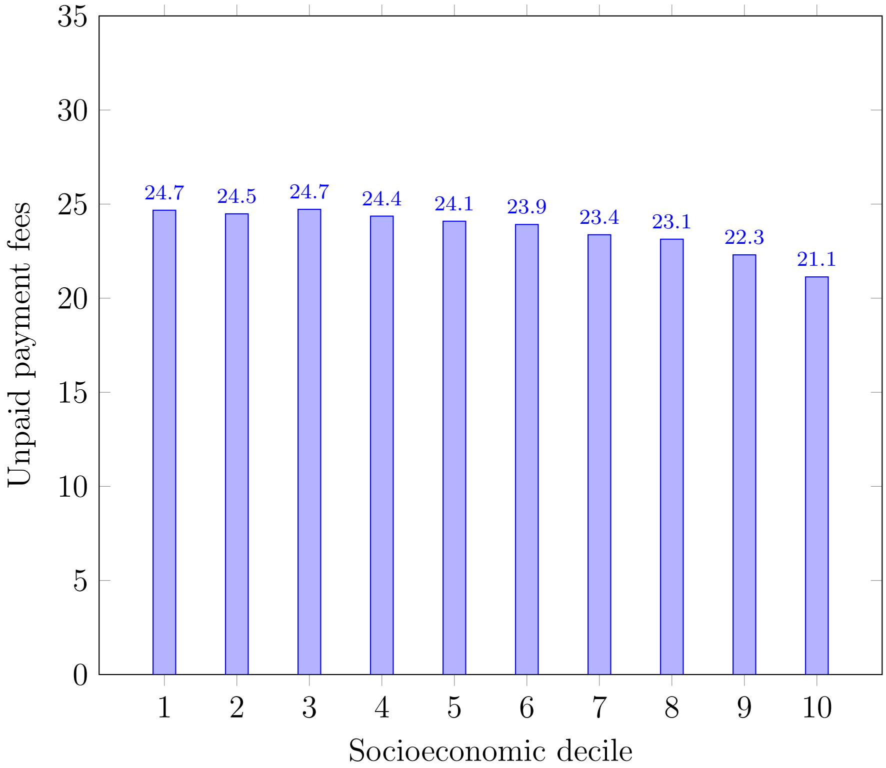
An average pay-on-demand user makes 2.702 repayments to pay-on-demand providers in a month; however, out of these 2.702 repayments, only 2.09 of these are successful. Hence, those repayments that failed lead to the occurrence of unpaid payment fees, which consequently increases the cost of accessing wages in advance. On the other hand, the average frequency of borrowing from pay-on-demand (Net Trans Loans) is only 1.22 times per month, so most users only used pay-on-demand once every month. The average amount they borrow is \$250.73 per month, and on average the users repay \$359.06.

Unpaid payment fees are proxies for using pay-on-demand successfully, as these costs together represent a major additional cost to access pay-on-demand beyond the "5% transaction cost". Although only it is only a \$5 cost each time, to minimise the credit loss rate the lenders send multiple direct debit requests to the users' accounts to ensure recollection, so the aggregate dishonours fees may accumulate to a substantial amount.

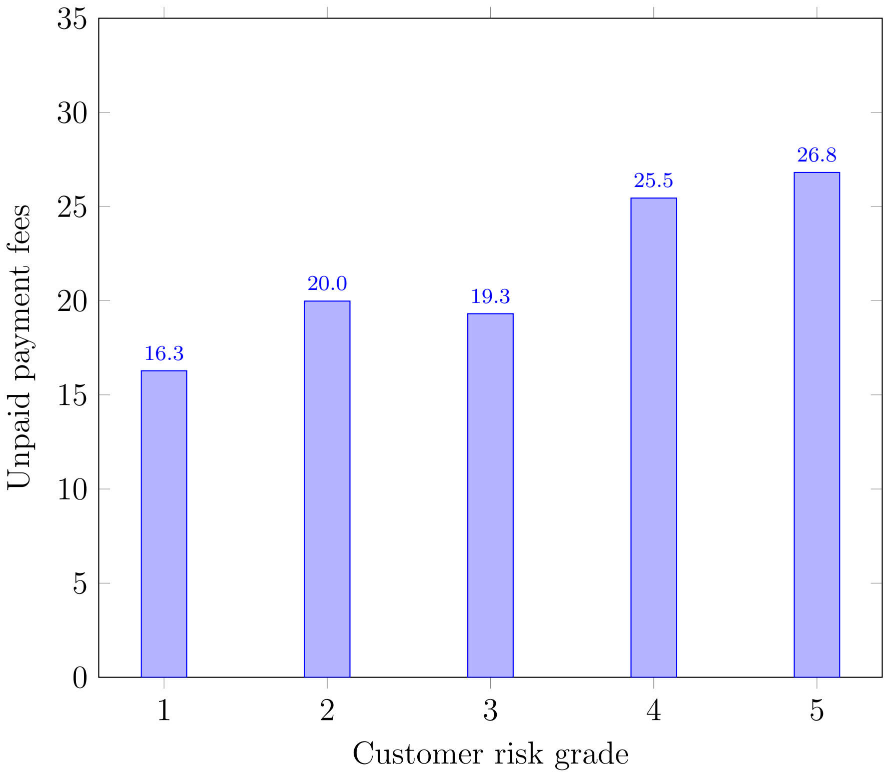
The more successful the usage, the less the unpaid payment fees. Overall, 46.51% of the users have incurred at least one unpaid payment fee on their accounts, and an average user is charged 2.702 unpaid payment fees in a month of use. Since on average they borrow \$250.73, the total unpaid payment fee ($\$2.702 \times 5 = \$13.51$) constitutes an economically significant cost to access the wages in advance, almost doubling the "5% transaction fee".

In Figure 10a, we plotted the average total dishonours fees incurred by people in different socioeconomic deciles. In all deciles, the average dishonours fees exceeded \$20, which represents a material cost of using the product. In addition, people from higher socioeconomic deciles incur less dishonours fees on average, so they are able to use the product more successfully.

Panel A: Distribution of unpaid payment fees by socioeconomic deciles



Panel B: Distribution of unpaid payment fees by customer risk grade



Panel C: Number of reversals for different salary types

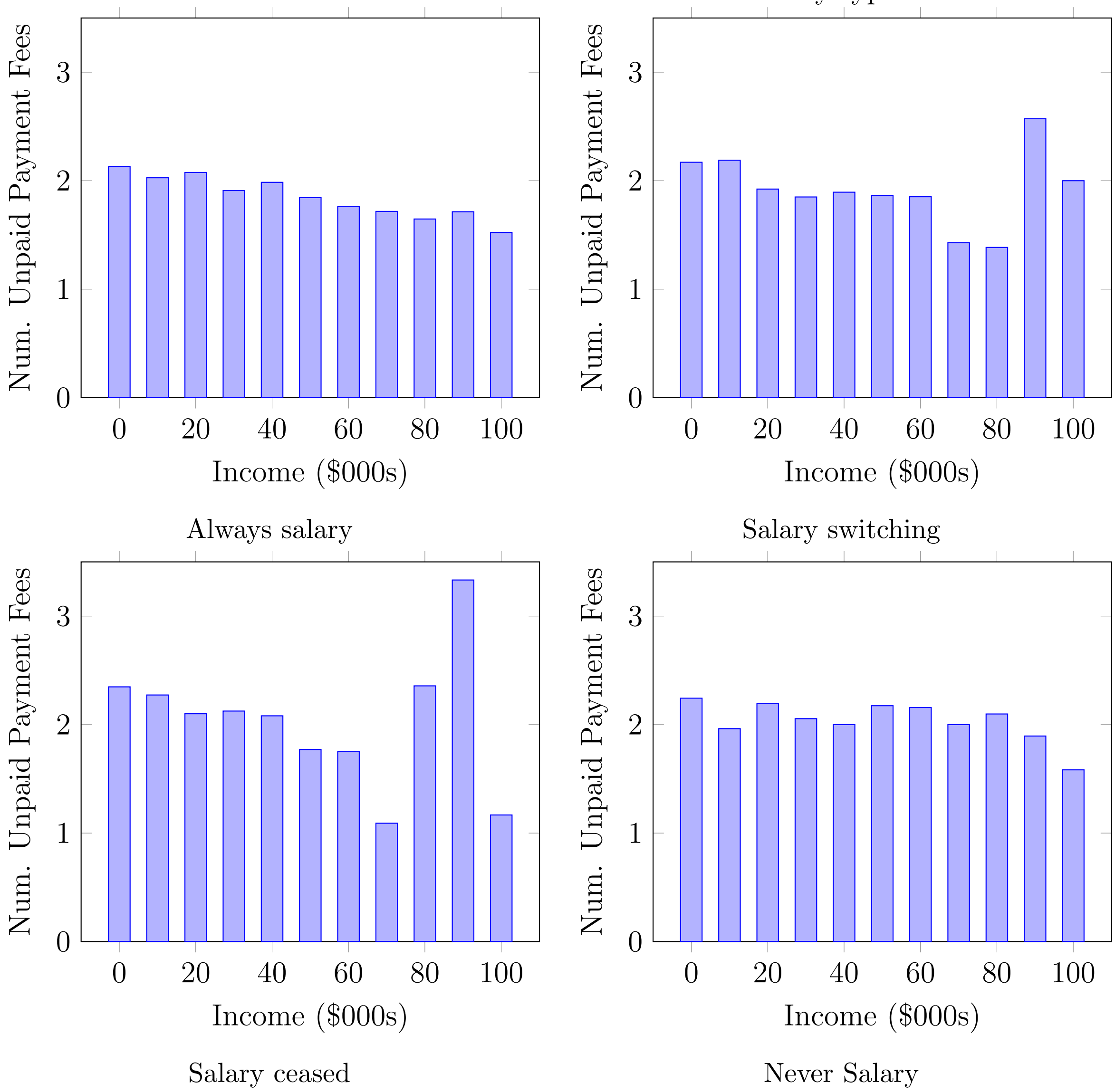


Figure 10: Risk grades and dishonour fees

Notes: This figure plots the distribution of unpaid payment fees. Panel A graphs the amount of unpaid payment fees paid by users from each socioeconomic decile. Panel B shows how much unpaid payment fees are paid by users from different risk grades. Panel C represents the amount paid payment fees paid by users of different income level and salary types.

On the other hand, people from different risk grades have also found varying success with the product. People with the highest credit risks (i.e. people from grade 4) on average received more than five unpaid payment fees, whereas people from the lowest risk level are charged dishonours fees less than four times. Notably, customers who are difficult to score incur the most amount of unpaid payment fees, paying $26.8 unpaid payment fees each month.

In panel C, I compared the distribution of unpaid payment fees for each salary types. Firstly, on average, people with constant salaries (under the *Always Salary* classification) can use the product more successfully than people with other types of salaries, incurring less unpaid payment fees per month in most income levels [7]. Second, among the users who always receive a salary and deposit the wage into the bank account, the higher their salaries are, the less unpaid payment fees they incur. Surprisingly, even among users earning more than 90K with adequate liquidity, on average they still incur an unpaid payment fee throughout the sample period.

Although pay-on-demand is to help bridge the cash flow timing mismatch between the paydays, users who experience the strongest payday effect and who should benefit the most from this new Fintech lending product are using the product least successfully. People earning lower wages and have lumpy wages on average incur more dishonours fees than those who earn more wages and have more stable earnings. This impose more costs on those who use pay-on-demand, which may ultimately limit the extent to which pay-on-demand can improve their financial stability.

5.3 Univariate tests

To better understand the structural differences between successful pay-on-demand users and the unsuccessful ones, I 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 users have incurred an unpaid payment fee.

The two groups are of a similar age and gender composition, averaging at 31 year old and having 40% female. Users that have incurred an unpaid payment fee are slightly more likely to be female (40.6% vs 39.6%), and are slightly younger (30.82 vs 30.95). The groups also differ in terms of their socioeconomic status, as users that have paid an

[7]Annual income is estimated by the CBA's algorithms, which pick up specific transactions that look like payments of wages. This estimate is only reliable for people always earning a salary, and less precise for other salary types. This may explain the spike around the $90,000 income level in the *Salary Ceased* graph.

		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
Credit Card Pre-Approval Score	23194	-117.129	159.27	26672	11.6963	147.48	-128.8253	<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.

unpaid payment fee are from slightly lower socioeconomic deciles (5.23 vs 5.34).

Consistent with hypothesis 4, people that have incurred a dishonours fees are from lower liquidity groups. They are more likely to never earned a salary or stopped receiving salary, and less likely to be always making a salary. On average, people with dishonours fees earn $4,320 less a year and have $582.73 less savings. The average savings level of the group with unpaid payment fees is less than half of savings of the group without unpaid payment fees. 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 a dishonours fee is incurred.

Supporting Hypothesis 5, the credit risks levels measured by the bank's private ratings also seem to be correlated with incurring unpaid payment fees. A comparison of the risk grade variables found that users that have incurred an unpaid payment fee are more likely to be from risk grade 4 and 5, meaning they are riskier and more difficult to score. They are also less likely to be from grade 1 and 2. However, caution should be exercised when interpreting such a difference in customer risk grade, as the unpaid payment fee may feed into the credit scoring algorithm. Nonetheless, for the other credit risk measurement variables, *behavioural risk score* and *credit card pre-approval score*, the groups that incurred unpaid payment fees have significant lower scores.

Other product holdings are similar between the two groups. 17.69% of the with unpaid payment fee group and 16.74% of the without unpaid payment fee group hold a credit card, a statically significant but economically insignificant difference. Similarly, the proportions of users with a personal loan are very close. Despite holding similar products, the actual uses of the products are very different between the two groups. Unsuccessful uses with other credit products such as a credit card are useful to predicting unsuccessful uses with pay-on-demand. Evidence for the said predictability includes failed pay-on-demand users having a higher average credit card utilisation rate and more past delinquency records. Users that failed pay-on-demand are twice as likely to have more than one past delinquency records on their credit cards, and much more likely to be under a financial hardship arrangement.

Successful users and unsuccessful users also exhibit different usage patterns. Consistent with the terms of uses, the credit accessible by the users are dynamic, which increases by each successful use and decreases by each unsuccessful use. Hence, we can observe that 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. On the repayment side, successful users make more successful payments to pay-on-demand lenders, as they have sufficient liquidity to ensure the success of a direct debit.

The differences *Num. Transactions Pmt* and *Net Trans Pmt* are indicative for the functionality of the salary link. On average, successful users have a higher *Net Trans Pmt*, but lower *Num. Transactions Pmt.* The differences are caused by failed payment to pay-on-demand lenders. When the lender tries to collect the receivable wages and a direct debit fails, several other requests are sent. These transactions also failed subsequently because the bank balances are less than the value of the debit. Hence, the total number of payments is higher for the unsuccessful users, but the number of successful ones is lower. Noticeably, the direct debit requests that after the first request have also failed, which accumulate to a high cost of borrowing. An average unsuccessful user is charged an unpaid payment fee 4.816 times (equivalently incurring $24.08 in unpaid payment fees) in one month. Since their average monthly borrowing is only $203.26, this increases the monthly finance cost by 11.85%.

The results in the univariate comparison lend support to Hypotheses 4 and 5, which predict who should be paying unpaid payment fees. 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 card successfully in the past or now, as they have lower utilisation rate and less previous delinquency records. Users who do not pay unpaid payment fees are also less likely to be in financial hardships arrangements, suggesting their use of credit is successful and they are maintaining regular repayments.

6 Research Design

6.1 Who is using pay-on-demand successfully?

To test hypothesis 4 and 5, I will use the transaction data of pay-on-demand users to estimate a logistics regression model. The dependent variable of the model is *Unpaid Payment Fee Flag*, which is a dummy variable equal to one if the customer has incurred an unpaid payment fee in month t. The regression will predict the probability of a user being charged an unpaid payment fee. The key explanatory variables of interest include *Hardship, Low Savings, Always Salary * ln(Income+1), CC Flag, CC Flag * CC Utilisation, CC Flag * CC Delinquency Bucket 1+/2+ and the Risk Grades.* I also control for the demographic information that may have explanatory power on *Num. Unpaid Payment Fee.*

$$
\begin{aligned}
\mathbb{P}(\text{Unpaid Payment Fee Flag}) = LOGIT(&\beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Gender}_i \\
&+ \beta_3 \text{Socioeconomic Decile}_{it} + \beta_4 \text{Savings>1000}_{it} \\
&+ \beta_5 \text{Always Salary} + \beta_6 \text{Always Salary} \times ln(\text{Income} + 1) \\
&+ \beta_7 \text{CC Flag}_{it} + \beta_8 \text{CC Flag}_{it} \times \text{High Utilisation}_{it} \\
&+ \beta_9 \text{CC Flag} \times \text{CC Delinquency Bucket 1+}_{it} \\
&+ \beta_{10} \text{CC Flag} \times \text{CC Delinquency Bucket 2+}_{it} \\
&+ \beta_{11} \text{Risk Grade 1}_{it} + \beta_{12} \text{Risk Grade 2}_{it} \\
&+ \beta_{13} \text{Risk Grade 4}_{it} + \beta_{14} \text{Risk Grade 5}_{it} \\
&+ \beta_{15} \text{Personal Loan Flag} + \beta_{16} \text{Hardship Flag} \\
&+ \beta_{17} \text{Benefit Flag})
\end{aligned} \tag{2}
$$

Income and variables related to credit card usage are included only as an interaction term. For income, the estimate is only reliable for users with a constant salary. Credit card usage variables are only available for users with a credit card, so they cannot be used as a standalone term. The hypothesis is tested by conducting a t-test on the coefficients of the explanatory variables. A summary of the prediction is reported in Table 4.

Hypothesis	**Variable**	**Anticipated sign**
H4:	Savings>1000	-
	Always Salary	-
	Always Salary * ln(Income+1)	-
H5:	CC Flag	-
	CC Flag * High Utilisation	+
	CC Flag * CC Delinquency Bucket 1+/2+	+
	Hardship	+
	Risk Grade 1	-
	Risk Grade 2	-
	Risk Grade 4	+
	Risk Grade 5	+

Table 4: Predicted signs of coefficients of Equation 2

As an additional robustness check, I would also re-estimate the model above, using an OLS. The independent variable will be the same, but the dependent variable is replaced by *Num. Unpaid Payment Fee.*

6.2 Who uses wage advances more?

Hypothesis 6 and 7 are tested by regressing the frequency and number of withdrawals in a month on the explanatory variables. The model specification is as follows. Consistent with the hypothesis, I expect opposite signs of the coefficients on socioeconomic decile, risk grade, savings balance and credit card utilisation rate in Equation 3 and 4. Regression is run on negative *Net Trans Sum Loan* because borrowings are credit to the accounts, so they appear as negative numbers in the transaction record.

$$\begin{aligned}
\text{-Net Trans Sum Loan}_{it} = &\beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Gender}_i \\
&+\beta_3 \text{Socioeconomic Decile}_{it} + \beta_4 \text{Savings>1000}_{it} \\
&+\beta_5 \text{Always Salary} + \beta_6 \text{Always Salary} \times ln(\text{Income} + 1) \\
&+\beta_7 \text{CC Flag}_{it} + \beta_8 \text{CC Flag}_{it} \times \text{High Utilisation}_{it} \\
&+\beta_9 \text{CC Flag} \times \text{CC Delinquency Bucket 1+}_{it} \\
&+\beta_{10} \text{CC Flag} \times \text{CC Delinquency Bucket 2+}_{it} \\
&+\beta_{11} \text{Risk Grade 1}_{it} + \beta_{12} \text{Risk Grade 2}_{it} \\
&+\beta_{13} \text{Risk Grade 4}_{it} + \beta_{14} \text{Risk Grade 5}_{it} \\
&+\beta_{15} \text{Personal Loan Flag} + \beta_{16} \text{Hardship Flag} \\
&+\beta_{17} \text{Benefit Flag} \qquad (3)
\end{aligned}$$

$$\begin{aligned}
\text{Net Trans Loan}_{it} = &\beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Gender}_i \\
&+\beta_3 \text{Socioeconomic Decile}_{it} + \beta_4 \text{Savings>1000}_{it} \\
&+\beta_5 \text{Always Salary} + \beta_6 \text{Always Salary} \times ln(\text{Income} + 1) \\
&+\beta_7 \text{CC Flag}_{it} + \beta_8 \text{CC Flag}_{it} \times \text{High Utilisation}_{it} \\
&+\beta_9 \text{CC Flag} \times \text{CC Delinquency Bucket 1+}_{it} \\
&+\beta_{10} \text{CC Flag} \times \text{CC Delinquency Bucket 2+}_{it} \\
&+\beta_{11} \text{Risk Grade 1}_{it} + \beta_{12} \text{Risk Grade 2}_{it} \\
&+\beta_{13} \text{Risk Grade 4}_{it} + \beta_{14} \text{Risk Grade 5}_{it} \\
&+\beta_{15} \text{Personal Loan Flag} + \beta_{16} \text{Hardship Flag} \\
&+\beta_{17} \text{Benefit Flag} \qquad (4)
\end{aligned}$$

A summary of the predicted coefficients is reported in Table 5 and 6. Hypothesis will be tested through conducting a t-test on the estimated coefficients at commonly accepted significance levels.

Hypothesis	Variable	Anticipated sign
H6:	Socioeconomic Decile	+
	Savings>1000	+
	Always Salary	+
	Always Salary * ln(Income+1)	+
	CC Flag	+

Table 5: Predicted signs of coefficients of Equation 3

Hypothesis	Variable	Anticipated sign
H7:	Socioeconomic Decile	-
	Savings>1000	-
	Always Salary	-
	Always Salary * ln(Income+1)	-
	CC Flag	-

Table 6: Predicted signs of coefficients of Equation 4

7 Stylised model of pay-on-demand

In Section 2.4, a simple model of pay-on-demand is shown for a cost-volume-profit analysis. The major drawback of the model is it features a uniform type of customers; however, pay-on-demand lenders provide different amounts of loans to borrowers of different risks level, so such an assumption is unrealistic. A model without such an assumption will provide more insights into the operation of pay-on-demand and the risks that the platforms and its users face. In this section, I will expand the stylised model to allow loan types to differ.

7.1 Single period model

Figure 11 gives a stylised model of pay-on-demand. The providers will receive the applications from two types of potential users of pay-on-demand. The "good" customers with a relatively low default rate per loan, and "bad" customers with a higher default rate per use.

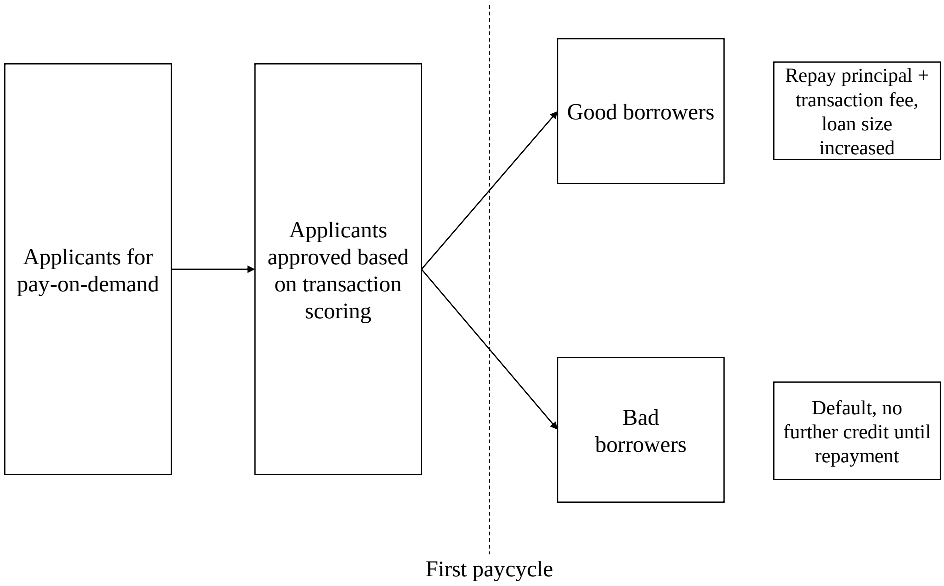


Figure 11: Stylised model of pay-on-demand screening

Let $\mathbb{P}(\text{Default}|\text{Good})$ and $\mathbb{P}(\text{Default}|\text{Bad})$ denote the probability that a loan lent to a good customer and a bad customer default respectively. Let p denote the probability that a randomly selected loan is lent to the good customer group. I further assume that each good customer, on average they borrow Amount_{Good} each time they use pay-on-demand, use pay-on-demand T_{Good} times throughout one year. For each bad customer, on average they borrow Amount_{Bad} each time, and they use pay-on-demand T_{Bad} times throughout one year.

Because good customers can advance a greater proportion of their wages, their total advancements in a given period will be greater. They should also make advances more frequently, as only customers who pay up are allowed to make advances. Overall, the good customers should represent a more profitable group of customers than the bad ones. The assumptions here are partly supported by the regression output in section 8. Users of lower credit risks, measured by CBA's proprietary algorithms, advance from pay-on-demand more frequently and borrow more per month.

The following assumptions are then made:

1. Assume that on average the good customers advance k times as much as the bad customers per loan.

$$\text{Amount}_{Good} = k * \text{Amount}_{Bad},\ k \geq 1 \tag{5}$$

2. Assume that the good customers advance g times as frequently as the bad customers.

$$T_{Good} = g * T_{Bad}, g \geq 1 \tag{6}$$

For each loan, the net profit is equal to the gross income from the loan, equal to $Amount \times 0.05$, less the sum of the expected credit loss, as calculated under the Basel Agreement (e.g., Matuszyk et al. (2010)) [8], and the allocated overhead cost to service the loan, which is a fixed percentage of the average loan size equal to $Amount * c$. Denote profit per loan to good and bad customer by $\mathbb{E}(\text{Net Profit}|\text{Good})$ and $\mathbb{E}(\text{Net Profit}|\text{Bad})$ respectively.

$$\begin{aligned}
\mathbb{E}(\text{Net Profit}|\text{Good}) =& (1 - \mathbb{P}(\text{Default}|\text{Good}))(0.05)(\text{Amount}_{Good}) \\
& - \mathbb{P}(\text{Default}|\text{Good}) * (\text{Amount}_{Good}) - c * (\text{Amount}_{Good}) \\
=& k * \text{Amount}_{Bad} * (0.05 - c - 1.05\mathbb{P}(\text{Default}|\text{Good})) \\
\mathbb{E}(\text{Net Profit}|\text{Bad}) =& (1 - \mathbb{P}(\text{Default}|\text{Bad}))(0.05)(\text{Amount}_{Bad}) \\
& - \mathbb{P}(\text{Default}|\text{Bad}) * (\text{Amount}_{Bad}) - c * (\text{Amount}_{Bad}) \\
=& \text{Amount}_{Bad} * (0.05 - c - 1.05\mathbb{P}(\text{Default}|\text{Bad}))
\end{aligned}$$

Expected profit per loan will simply be the average of the profit on good loans and bad

[8] An implicit assumption here is that the loss given default (LGD) is set to 100%, that there will be no recovery given default. Given that pay-on-demand lenders send several direct-debit requests to collect the advanced wages, the recovery rate for a loan that could not be honoured will be very low. The LGD, in reality, should be very close to 1.

loans, weighted by the proportion of loans of each type.

$$\mathbb{E}(\text{Net Profit}) = p * \mathbb{E}(\text{Net Profit}|\text{Good}) + (1-p) * \mathbb{E}(\text{Net Profit}|\text{Bad}) \tag{7}$$

We could also calculate the credit loss rate, which is the ratio of the expected credit loss expense to the expected loan size. The expected credit loss expense is given by Equation 8. Let $x = \mathbb{P}(\text{Default}|\text{Good})$ and $y = \mathbb{P}(\text{Default}|\text{Bad})$

$$\text{Credit Loss Rate} = \frac{k * x * p + y * (1-p)}{kp + (1-p)}, \tag{8}$$

At the break even point, the expected profit per loan is equal to zero. To calculate the break-even point, set Equation 7 to zero and solve for p:

$$\begin{aligned} 0 &= p * k * \text{Amount}_{Bad} * (0.05 - c - 1.05x) \\ &\quad + (1-p) * \text{Amount}_{Bad} * (0.05 - c - 1.05y) \end{aligned} \tag{9}$$

Since $Amount_{Bad} > 0$, solve for p:

$$p = \frac{1.05y - 0.05 + c}{(0.05 - c)k - 1.05xk + 1.05y - 0.05 + c} \tag{10}$$

Since good users advance g times as frequently, the proportion of good users to bad users is given by:

$$\frac{p}{g(1-p)} \tag{11}$$

The proportion of good users to total users is given by:

$$\frac{p}{p + g - pg} \tag{12}$$

For example, assume that the average size of advancement of a good loan is the same as that of a bad loan, $k = 1$, and $c = 1.25\%$ the lenders need to achieve the following to break even:

1. The default rate on a good loan is less than 1% ($\mathbb{P}(\text{Default}|\text{Good}) < 1\%$).

2. The default rate on a bad loan is less than 20% ($\mathbb{P}(\text{Default}|\text{Bad}) < 20\%$).

3. The proportion of loans to good users is higher than 86.47% ($p > 86.47\%$).

Conditional that the lenders achieve the targeted value of p, the default rate, which is equal to the weighted average default rate of the good loans and the bad loans, is given by:

$$\begin{aligned}\mathbb{P}(\text{Default}) &= \mathbb{P}(\text{Default}|\text{Good}) * p + \mathbb{P}(\text{Default}|\text{Bad}) * (1 - p) \\ &= 1\% * 86.47\% + 20\% * (1 - 86.47\%) = 3.57\%\end{aligned}$$

At the break-even point, this default rate above can be interpreted as the threshold default rate that pay-on-demand lenders need to stay below. Any default rate higher than this will imply a loss. At the current level, this given default rate threshold is slightly higher than the targeted default rate in *Beforepay*'s replacement prospectus, which is 3%. Suppose k,$\mathbb{P}(\text{Default}|\text{Good})$ and $P(\text{Default}|\text{Bad})$ can meet the requirements above, achieving a default rate of 3% will make a profit for *BeforePay*.

Conditional on breaking even, the credit loss rate defined by Equation 8 only changes with respect to c. Substituting Equation 10 into Equation 8 will eliminate k, x and y.

$$\mathbb{E}(\text{Credit Loss Rate}|\text{Net Profit} = 0) = \frac{1 - 20c}{21} \tag{13}$$

Intuitively, when the expected profit per loan is equal to zero, the credit loss rate must be equal to the net return of servicing each loan, which is affected by the difference between the income of each loan ($5\% * \mathit{Amount}$) and the cost ($c * \mathit{Amount}$).

7.2 Sensitivity Analysis

7.2.1 Sensitivity of p to exogenous parameters

The model in the previous section featured the exogenous variables including c, x, y, k, and the endogenous variables including p, default rate and credit loss rate. In this section, we will present several stylised facts about the pay-on-demand business model, through a sensitivity analysis of the endogenous variables. In all the analysis, we set the base case to be $c = 1.25\%, x = 1\%, y = 20\%$ and test how p changes with respect to k.

Figure 12 plots the proportions of good loans required to break even against k, the ratio of the average loan size of a good loan to a bad loan. Repeated users represent a very profitable group of customers for the pay-on-demand industry, evident by the sensitivity of p to changes in k. All the curves feature a negative slope and are strictly decreasing, suggesting that a higher value of k reduces the proportion of good loans required to break even. Holding all else constant (g), there is less pressure imposed on the screening algorithm to accurately identify good users, and there is a higher range of default rate that the companies could make a profit.

In Figure 12a, we plot p as a function k, and we varied the values of x to see how changes in the riskiness of the good users may affect the profitability of the pay-on-demand model. x may change, for example, if there is an update to the direct debit algorithm that makes the estimation of the pay-on-demand wages more accurate, or an exogenous shock such as a natural disaster attracts different types of users to use pay-on-demand. As x increases, the upward shift in the curves suggests a higher value of p is required to break even for all values of k. If the good users became riskier, there is increased pressure on the accuracy of the screening algorithm, as more good users are required to offset the loss made by the bad users. Or, the good users need to borrow more from the product to offset the impact. It is also noteworthy that as k increases, the differences of p caused by the same change in x also increase. The heavier repeated uses amplify the impact caused by an increase in the default rate by the good users.

In Figure 12b, we tested how the relationship between p and k changes if y changes. A similar impact to changing x can be observed. An increase in y requires an increase in the proportion of good users to break even, thereby shifting the curve upwards. The differences in p are higher if k is higher. Different to the scenario of changing x, an increase in y causes less impact than a decrease in y of the same size.

Finally, we consider how changes in the fixed cost of operating will affect p at the break-even point. c is the allocated overhead cost to each loan, represented as a proportion to the size of each loan. An example of scenarios in which the allocated overhead cost will increase is the lenders becoming more risk averse and lending out fewer loans. Since the number of loans is lower, there will be a higher fixed cost per loan. The impact of such changes is shown in Figure 12c. Holding all else constant, an increase in fixed cost per dollar of loan served increases the proportion of good loans to break even. Doubling the fixed cost is more influential than halving the fixed cost.

7.2.2 Sensitivity of credit loss rate to exogenous parameters

Given that *BeforePay* is still making a loss as at the most recent financial year end,[9] the assumption that pay-on-demand breaks even may limit the usefulness of the model. Hence, this section reports a sensitivity analysis of the credit loss rate, without the break-even assumption. In the remainder of this section, we implore a sensitivity analysis to test how the credit loss rate varies for different values of k, but unlike section 7.2.1, the following analysis will treat p as an exogenous parameter equal to 0.8647 in the base case. The base case for the analysis is $p = 84.67\%$, $c = 1.25\%$, $x = 1\%$, and $y = 20\%$.

In Figure 13, we plot the credit loss rate against k, the ratio of average loan amount for good users to bad users. As k increases and repeated users employ pay-on-demand more heavily, the aggregate credit loss rate is lower. This is because the lower default rate of the good users subsidises the higher default rate of the bad users. Therefore, to

[9] Refer to `https://www.beforepay.com.au/investor-hub/financial-reports` for the most recent financial report of *BeforePay*. Since *MyPayNow* is not publicly listed, the financial information of the company is very limited.

remain a going concern and achieve the targeted credit loss rate, the providers need to ensure they have a cohort of heavy repeated users.

The credit loss rate reacts very similarly to how p does, given the same change in exogenous parameters. Figures 13a and 13b show that, for an increase in the default rate by bad users, the credit loss rate is only substantial when k is low. Thus, a growing cohort of repeated good users is needed to offset the increasing credit risks of the bad users. In Figure 13b, we varied the value of p and found that a higher proportion of good users reduce the total credit loss rate. However, as k increases, the benefit of having a higher p gradually decreases.

7.3 Value of a good screening algorithm

With Equation 7, it is intuitive why an effective screening algorithm is crucial to the profitability of the industry. In this context, screening adds value to lenders of pay-on-demand, as it increases the proportion of good loans p, which on average makes money for the providers. A perfect screening algorithm should have filtered out all the bad borrowers, so $p = 1$.

However, making a screening algorithm more accurate does not necessarily imply increased profitability for the industry. The benefit of improving screening accuracy is increasing the value of p, which reduces the total credit loss rate, but the cost of it is an increased cost to service, c. The increase is caused by two factors: (1) a more advanced screening algorithm is more costly to maintain and manage, and (2) the reduction in the total volume of loans serviced means more fixed costs will be allocated to each loan.

Hence, we want to investigate under what circumstances are the screening algorithm more valuable to the lenders. In this context, a more valuable algorithm should reduce the credit loss rate by a greater extent, given a fixed improvement in p. This means minimising the partial derivative for credit loss rate with respect to p, $\frac{\partial}{\partial p}$.

Take the partial derivative of credit loss rate with respect to p:

$$\frac{\partial}{\partial p}(\text{Credit Loss Rate}) = \frac{k(x-y)}{((k-1)p+1)^2} \tag{14}$$

Two important observations can be made. Firstly, the derivative is always negative, given reasonable values of parameters ($x < y$). An increase in p always reduces the credit loss rate. Second, when $k = 1$, the partial derivative is equal to a constant. For values of k greater than 1, the derivative is smaller for higher values of p, meaning the credit loss rate is a convex function of p. As p increases, the marginal benefit of stricter screening p is smaller. Thirdly, the greater the difference between the good and bad users, the smaller the derivative, so the screening algorithm is more valuable when good users differ from bad users significantly.

Depending on p, k may increase or decrease the value of the partial derivative. Equation 15 is the second order derivative of the credit loss rate, with respect to p and k.

$$\frac{\partial}{\partial p \partial k}(\text{Credit Loss Rate}) = \frac{(kp+p-1)(x-y)}{((k-1)p+1)^3} \tag{15}$$

Since $x < y$ and $k \geq 1$, the second order derivative is negative when $kp + p - 1 > 0$, and positive when $kp + p - 1 < 0$. For larger values of p such that $kp + p - 1 > 0$, an increase in k will reduce the value of a good screening algorithm. Alternatively, for smaller values of p such that $kp + p - 1 < 0$, an increase in k will increase the value of a good screening algorithm. In Figure 14, the plots of default rate against p support the observations above. The default parameter values are $k = 2, x = 0.01, y = 0.2$, and $c = 0.0125$. For all the cases, the required p value to break even is very high, ranging from 68% to 90%.

8 Results

8.1 Who pays unpaid payment fees?

I first estimated a model with the specification in Equation 2, to examine the determinants of incurring an unpaid payment fee. Both logistic regressions and OLS regressions are used, allowing us to examine the likelihood of and incurring unpaid payment fees, and the level of unpaid payment fees, respectively. Table 7 outputs the result for the regressions. Columns (1) to (5) of Table 7 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 7 I estimate an OLS regression, with *Num. Unpaid Payment Fees* being the dependent variable. In Table 7, I 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), I 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 7, Column (6) includes the complete set of independent variables.

The results of the logistic regression models shown in Table 7 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 lower *Socioeconomic 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

	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	-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 7: 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.

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 7) 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% 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.[10] 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 7. However, neither of these two models include information about the usage of the credit card. Model specifications (3) and (4) of Table 7 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), is not related to unpaid payment fees.

[10]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 $e^{0.127/0.024} = \$198.34$.

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 1+*) 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, noting that users who have been in Bucket 2 or higher will also have appeared in Bucket 1 or higher. The net coefficient for a credit card holder who has been in bucket 2+ is $(-0.599 + 0.444 + 0.525) = 0.370$, which is 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 different risk grades, which are bank's private evaluations of the customers' credit risks, have different odds of paying an unpaid payment fees, as reported by specification (5) and (6) in Table 7. 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.

In addition, the inclusion of risk grade indicators have significant impact on other coefficients, as the bank's risk grades incorporate information related to customer's *Socioeconomic Decile*, *CC Flag*, *DD Delinquency Bucket* and *Utilisation Rate*. Hence, the inclusion of the term has turned socioeconomic decile insignificant in column 5. The coefficients of the *CC Flag * Highly Utilised* and *CC Flag * CC Delinquency Bucket 1+* has also been changed significantly.

It is also worth noting that the introduction of the risk grade variables has significantly improved the model predictability, evidenced by the significant improvement in pseudo R^2 from model 4 to 5 (from 0.046 to 0.120). Such predictability is likely caused 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 assess only two months of information, whereas the bank incorporates information of longer time to develop the risk grades. Performing credit checks may lead to a substantial improvement in loan profitability, caused by an increased effectiveness of screening.

Overall, the results in Table 7 lend support to hypothesis 4 and 5. Hypothesis 4, which predicts negative coefficients on *Savings>1000*, *Always Salary* and *Always Salary * ln(income+1)*, is supported by the results in Table 7. In all columns, negative coefficients on *Savings>1000* and Income are found, which suggests that users with less savings and income pay more unpaid payment fees. As for the prediction on *Always Salary*, although only Column (1) returned a negative coefficient, and Columns (2) to (6) all reported positive coefficients, there is still sufficient evidence to suggest that users under *Always Salary* classification pay less unpaid payment fees, because the critical value of income that makes the *Always Salary* group more likely to pay unpaid payment fees is extremely low.

In terms of hypothesis 5, we have found evidence that given a successful use history of credit cards (not highly utilised and less than 2 past delinquency record), having a credit card is negatively related to incurring an unpaid payment fee, as the coefficients on *CC Flag* is negative (see Table 7 Column (3) to (5)). Given that past credit card delinquencies and credit card utilisation rate are correlated with the risk grades and *Hardship*, I refer to Column (3) to test the hypothesis related to credit card utilisation and past delinquencies. Credit card users with greater than 95% utilisation rate, and those with past delinquency records are more likely to pay unpaid payment fees, compared to credit card users who do not. Consistent with the predicted coefficient on *Hardship* in Table 4, Columns (4) to (6) of Table 7 suggest that users who are under a hardship arrangements are more likely to pay unpaid payment fees. Safer bank customers (i.e customers in risk grade 1 and 2) incur less unpaid payment fees than customers in grade 3, 4 and 5, evident from the sign and magnitude of the coefficients on *Risk Grade 1-5*.

8.2 Who uses pay-on-demand more?

In this subsection, I test the hypotheses related to the intensive margins of pay-on-demand, through OLS regressions on the monthly frequency of accessing pay-on-demand (*Net Trans Loan*) and amount of withdrawals of pay-on-demand (*Net Trans Sum Loan*) in a month. In a similar vein to the previous section, I 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) I include more explanatory variables including income (2), credit card utilisation status (3), other product co-holding information (4) and credit risks indicators (5). Table 9 reports the estimation outputs for the frequency of withdrawals, and Table 8 presents the results of the regression on the amounts of withdrawals.

8.2.1 Amount of withdrawals

The results in Table 8 indicate that *Age* is also a determinant of the intensive margins. In all columns in Table 8, the coefficients on *Age* is significant, suggesting 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 wages withdrawals. This trend is opposite to how age is related to the probability of using the product, as previous analysis has shown that this product is predominantly used by the younger population. The socioeconomic deciles of the customer's residence is also positively related to the amount borrowed from pay-on-demand. On average, a user in decile 10 will borrow \$27.423 per month from pay-on-demand (according to Column (1)). An explanation for this trend is that people from higher socioeconomic deciles are assessed as safer customers by pay-on-demand, so they are allowed to access a greater proportion of their wages. On the other hand, how gender affects the intensive margins is consistent with the extensive margin. A significant and negative coefficient on *Gender* is reported in all columns, both before and after controlling for the customer risk grade. This can be interpreted as males withdraw \$25.377 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), I only include the variables that pay-on-demand providers can access as the explanatory variables, and 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. Noticeably, the magnitude of the coefficients is decreasing as more sets of control variables are incorporated into the model. In the model with the most complete set of independent variables, users with more than \$1,000 of savings only borrow \$8.190 more, and this difference is only significant at 10% significance level. Similarly, users who always deposit their salaries into their savings account borrow \$67.403 more from pay-on-demand [11] as per Model (1), and users with higher income borrow more. For example, based on the specification of Model (5), users with 1% more income borrow \$0.07434 per month. 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.

[11] Although the inclusion of *Always Salary * log(Income+1)* has turned 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	-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 8: 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. Robust standard errors are reported in the brackets.

Next, we examine the variables related to the credit card usage. All Columns of Table 8 evidence that people with a credit card tend to borrow more from pay-on-demand. In Column (1) of Table 8, 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 these variables are included (in Columns (3) to (5)), the magnitude of the coefficients on *CC Flag* has increased, as users with unsuccessful credit card usage history tend to withdraw less from pay-on-demand. Even after controlling for the credit risks (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 of Column (3), which includes the interactions terms of *CC Flag* and credit card usage variables including *CC Delinquency Bucket* and *Highly Utilised*, indicate that both defaulting on credit cards more than once and having a highly utilised credit card means less access to pay-on-demand compared to users with a credit card. Pay-on-demand credit card holders who default once on their credit card debt borrow \$10.846 less than credit card holders who never defaulted, but they still borrow \$55.347 more than those pay-on-demand users without a credit card. It is only when the users have defaulted on more than once (both *CC Delinquency Bucket 1+* and *CC Delinquency Bucket* 2+=1) that they borrow slightly less than a borrower without a credit card. After controlling for the demographic and socioeconomic variables (Model (3)), users with a highly utilised credit card borrow \$19.707 less per month compared to users whose credit cards are not highly utilised.

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 8, 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. Nonetheless, suppose the users have failed to meet their financial obligations on these products and arranged a financial hardship arrangement, these users borrow much less from pay-on-demand per month. Columns (4) and (5) also indicate that users with a hardship arrangements on average borrow \$41.557 and \$41.964 less compared to those without a hardship arrangements, before and after controlling for their credit risk grades.

Column (5) of Table 8 has shown that users of various customer risk grades borrow different amounts from pay-on-demand. Safer bank customers (i.e., those from *Risk Grade 1* and *Risk Grade 2*) borrow more from pay-on-demand, and riskier bank customers borrow less. Compared to a pay-on-demand user from Risk Grade 3, users from grade 1 and 2 borrow \$40.630 and \$22.453 per month, whereas users from grade 4 borrow \$31.532 less. Users who are difficult to rank 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 can produce similar results to a credit check.

The benefit indicator variable, *Benefit Flag*, is negatively related to the amount of pay-on-demand borrowings. Although this variable is not significantly correlated with the occurrence of unpaid payment fees, Column (4) reports that users who are unemployed and under benefits borrow \$41.557 less per month. This is caused by pay-on-demand lenders ceasing the users' credit before they use it unsuccessfully

Overall, the results here are consistent with the results in Table 7. 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. The coefficients on the *Socioeconomic Decile*, *Savings>1000*, *Always Salary*, *Salary Salary * ln(Income+1)* and *CC Flag* are consistent with the prediction summarised in Table 5, so hypothesis 6 is supported by these results.

8.2.2 Frequency of withdrawals

In Table 9, I employ a similar OLS regression model that features the number of pay-on-demand borrowings in a month *Net Trans Loan* as the dependent variables while keeping the independent variables the same for all columns. A comparison of the results in Table 8 and Table 9 reveals that the most factors that affect the total amount of borrowings also influence the frequency of borrowings in a similar way. However, for *Age, Socioeconomic Decile* and *Savings>1000* variables, I have also found that they impact the frequency and amount of borrowings differently. The relative magnitude of the estimated coefficients on the credit card related variables are also different in the frequency and the amount regression.

Age, which is positively related to the amount of wages accessed in advance, appear to be negatively correlated with the frequency of borrowings, based on the results in Columns (1) to (4) in Table 9. Despite being statistically significant, the coefficients on *Age* are economically insignificant, as a ten year increase in age is only associated with a 0.02 times reduction in the monthly frequency of use. After controlling for the credit risks variables in Column (5), age is no longer associated with the frequency of use.

In terms of socioeconomic decile, Table 8 has reported a significant and positive coefficient, but Table 9 reported insignificant coefficients for all columns. Users from a higher socioeconomic decile borrow more money from pay-on-demand; however, surprisingly, their usage frequency does not differ significantly.

The coefficients on *Savings>1000* are opposite in Table 8 and 9. Pay-on-demand users whose deposit savings balance exceed $1,000 borrow $28.375 more per month, but the monthly frequency of access is 0.194 less based on the specification in Column (1) of both tables; hence, their average loan size must be greater compared to customers without $1,000 of savings.

The extent to which having a credit card affects the amount withdrawn and the frequency of withdrawals is also different. Examining how holding a credit card affects the frequency of usage, it is found that without controlling for the past delinquencies and

	Net Trans Loan				
	(1)	(2)	(3)	(4)	(5)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	-0.055***	-0.051***	-0.051***	-0.049***	-0.049***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Socioeconomic Decile	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Savings>1000	-0.194***	-0.196***	-0.201***	-0.228***	-0.272***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Always Salary	0.121***	-0.129***	-0.129***	-0.129***	-0.127***
	(0.013)	(0.023)	(0.023)	(0.023)	(0.023)
Always Salary*log(Income+1)		0.027***	0.027***	0.025***	0.024***
		(0.002)	(0.002)	(0.002)	(0.002)
CC Flag	-0.012	-0.018	0.091***	0.055	0.038
	(0.017)	(0.017)	(0.034)	(0.034)	(0.034)
CC Flag * CC Delinquency Bucket 1+			-0.028	0.071*	0.145***
			(0.037)	(0.037)	(0.037)
CC Flag * CC Delinquency Bucket 2+			-0.116***	-0.028	-0.021
			(0.043)	(0.044)	(0.044)
CC Flag * Highly Utilised			-0.099***	-0.078**	-0.044
			(0.038)	(0.038)	(0.038)
Risk Grade 1					0.167***
					(0.026)
Risk Grade 2					0.077***
					(0.022)
Risk Grade 4					-0.146***
					(0.019)
Risk Grade 5					-0.226***
					(0.018)
Personal Loan Flag				0.127***	0.106***
				(0.021)	(0.021)
Hardship Flag				-0.306***	-0.183***
				(0.018)	(0.019)
Benefit Flag				-0.075***	-0.077***
				(0.029)	(0.029)
Constant	1.268***	1.278***	1.277***	1.302***	1.321***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)
N	49,866	49,866	49,866	49,866	49,866
R^2	0.004	0.006	0.008	0.012	0.019
Adjusted R^2	0.004	0.006	0.006	0.012	0.018
Residual Std. Error	1.433 (df=49859)	1.431 (df=49858)	1.431 (df=49855)	1.427 (df=49825)	1.422 (df=49848)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 9: Predictors of the number of pay-on-demand borrowings

Notes: This table presents the OLS regression that uses the demographic, socioeconomic, other product co-holding and credit risk variables to predict the frequency of using pay-on-demand in one month. Robust standard errors are reported in the brackets.

utilisation rates, having a credit card does not affect the frequency of usage (see Column (1) and (2) of Table 9). In contrast, just having a credit card by itself is associated with a higher amount of wages accessed in advance. Additionally, Column (3) of the two tables also suggest that the relative magnitudes of the *CC Flag* interaction terms are different. In terms of the frequency of use, if a user either defaulted on their credit card repayment more than once, or has a highly utilised card, their frequency of access will be lower compared to the pay-on-demand users without a credit card. In contrast, in the model for *Net Trans Sum Loan*, only credit card users who both defaulted more than once and have a highly utilised credit card borrow less from pay-on-demand compared to users without a credit card.

Only part of hypothesis 7 is supported by the results in Table 6. I only found evidence that users with more than $1,000 of cash balance in their debit account use pay-on-demand less frequently. They can use their savings balance to smooth out a liquidity mismatch, which is cheaper than pay-on-demand. For all the other coefficients that I have made specific prediction for (see Table 6), the estimated coefficients as reported in Table 6 are either statistically insignificant or of an opposite sign to the prediction. There is also insufficient evidence to conclude that users who are always making a salary borrow less frequently because the critical value of income at which users under the *Always Salary* classification become more frequent users is too low.

9 Discussion and conclusion

In this thesis, I 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, claiming only to charge 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)), I 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, I 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 have 73% have been delinquent on their card in the previous 12 months. Thus, pay-on-demand users with credit cards demonstrate signs of financial stress. Users of pay-on-demand without a credit card may face difficulties in obtaining one, given their low *Credit Card Pre-Approval Score*.

I then 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 pays 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, I 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 poorer postcodes. 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 (e.g. 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, I 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. I 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. My theoretical model shows that repeated use by good borrowers is required for pay-on-demand platforms to sustain profitability.

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, will also include the recent financial hardship arrangements in the 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 have a damaged credit reputation. A reduction in volume will increase administration costs per loan, driving down the expected profits. If it is not in the lenders interest to impose a credit check, regulatory interventions may be required.

Since pay-on-demand lenders can only charge the flat 5% interest and there is no room for altering interest rates, to ensure the pay-on-demand business model remains profitable requires users to borrow a greater amount and borrow repeatedly. 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. Frequency of use, however, is less predictable, likely due to the limitations of the sample.

Future research should examine in greater detail the motivation for people to take out a pay-on-demand wage advancement. 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 wellbeing (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.

10 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.
Behavioural Score	A measurement of the customer's credit risk, the higher the value, the riskier the customer is.
Benefit Flag	A dummy variable equal to one if the customer is unemployed and is receiving an unemployment benefit.
CC Delinquency Bucket 1+ (2+)	An indicator equal to one if the customer has at least 1 (2) credit card delinquency record in the last 12 months. 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.
CC Pre-approval Score	This variable is used to make decisions on the customers' applications for a credit card. The higher the value, the more likely that a customer's application will be approved.

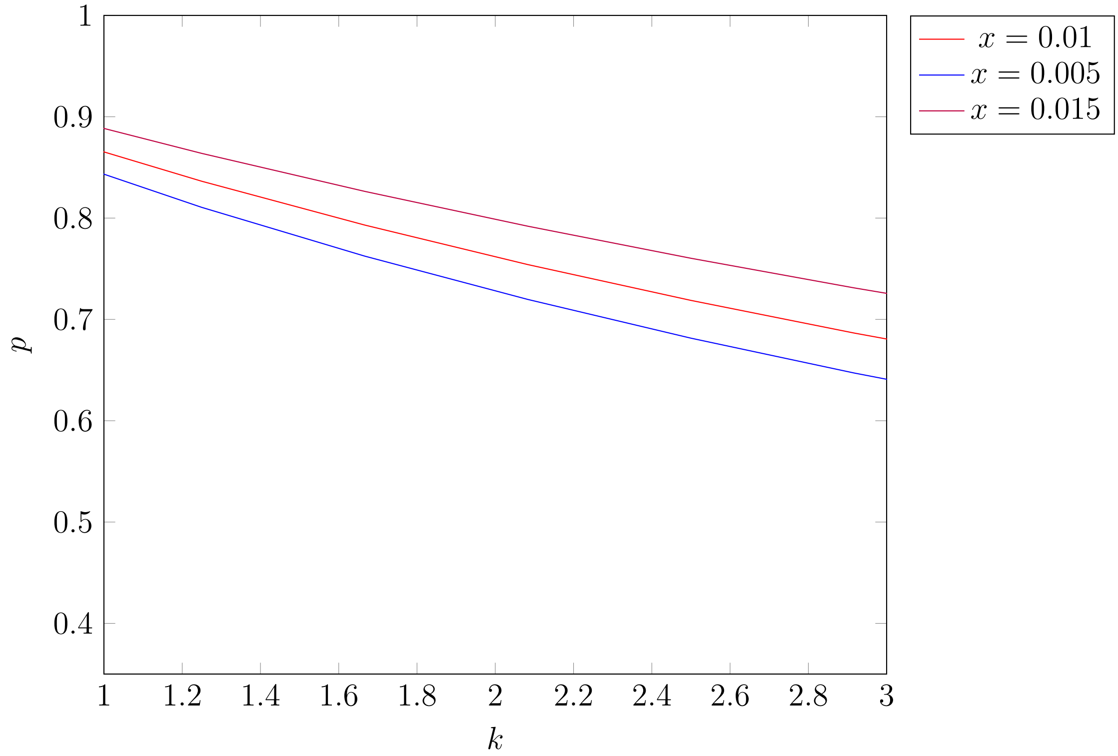
Customer Risk Grade	The risk grade is a categorical variable assigned to the customers, based on the quintile that their behavioural scores are in. The scores are given based on the bank's internal grade algorithm. The higher the risk grade, the higher the risks of the customers. For example, customers 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, according to the **CommScore** database. This estimate is produced by the CBA 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 CBA.
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 CBA 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.

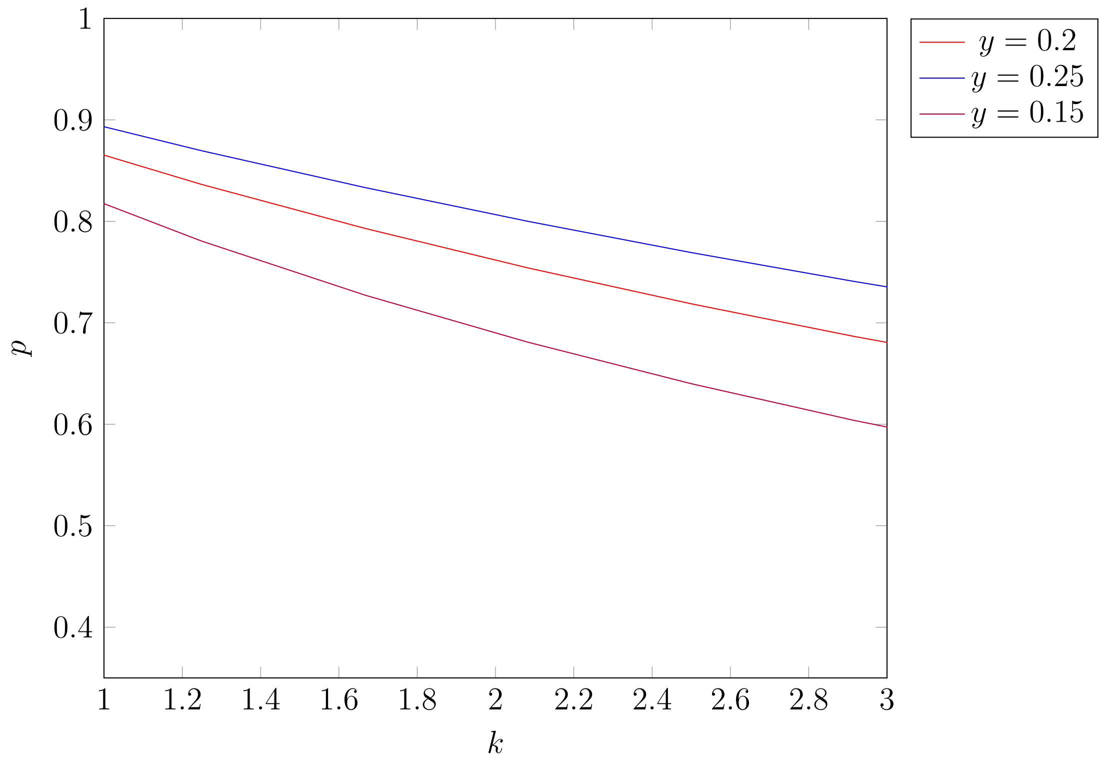
Socioeconomic Decile	The socioeconomic decile of a customer's address. The decile is calculated by matching the postcode of the address with the Australian Bureau of Statistics (ABS) "Socioeconomic Index for Areas" Index of Advantage and Disadvantage (2016) ranking of every postcode. The decile ranges 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 10: Variables definitions

Panel A: Sensitivity analysis of p to x



Panel B: Sensitivity analysis of p to y



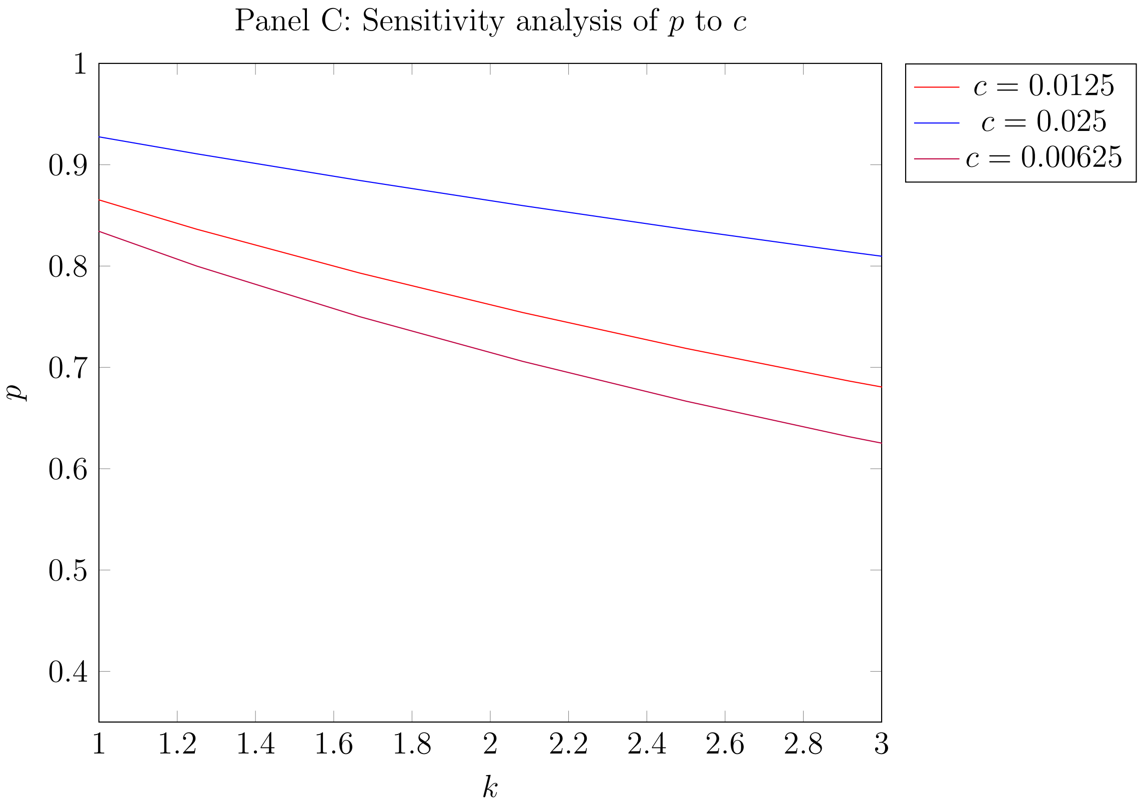
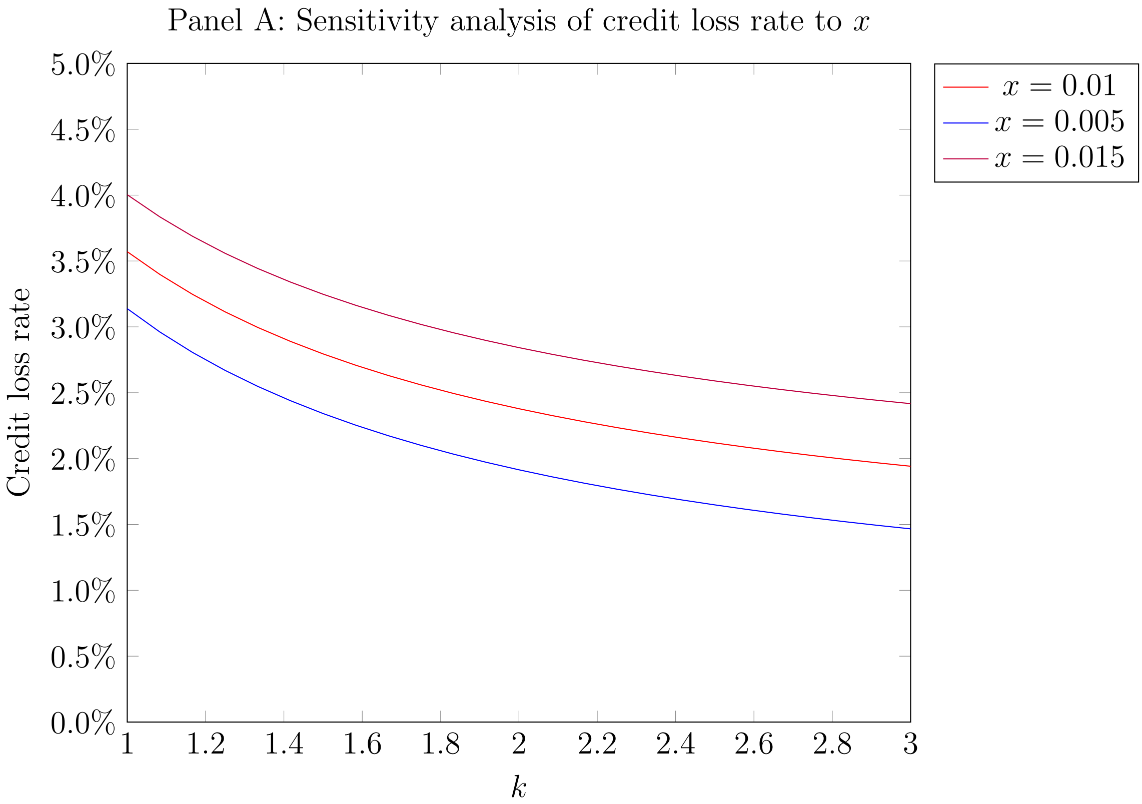
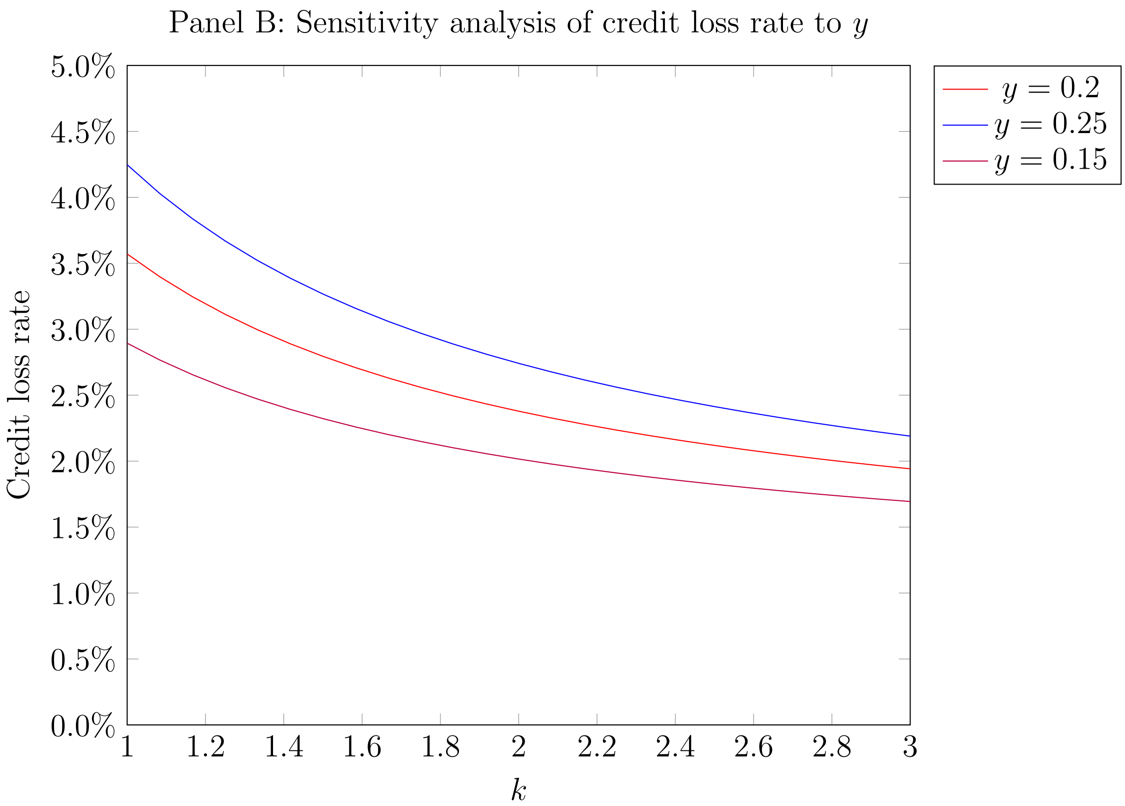


Figure 12: Sensitivity analysis of p to k

Notes: This figure plots the sensitivity analysis of the proportion of loans to good customers required to break-even, to changes in k. In each panel, we set the base case to $c = 1.25\%, x = 1\%, y = 20\%$, represented by the red curve. Panel A, B and C show how the sensitivity of p to k responds to changes in x, y and k respectively.


Panel A: Sensitivity analysis of credit loss rate to x
Credit loss rate
5.0%
4.5%
4.0%
3.5%
3.0%
2.5%
2.0%
1.5%
1.0%
0.5%
0.0%
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
k
$x = 0.01$
$x = 0.005$
$x = 0.015$


Panel B: Sensitivity analysis of credit loss rate to y
Credit loss rate
5.0%
4.5%
4.0%
3.5%
3.0%
2.5%
2.0%
1.5%
1.0%
0.5%
0.0%
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3
k
$y = 0.2$
$y = 0.25$
$y = 0.15$

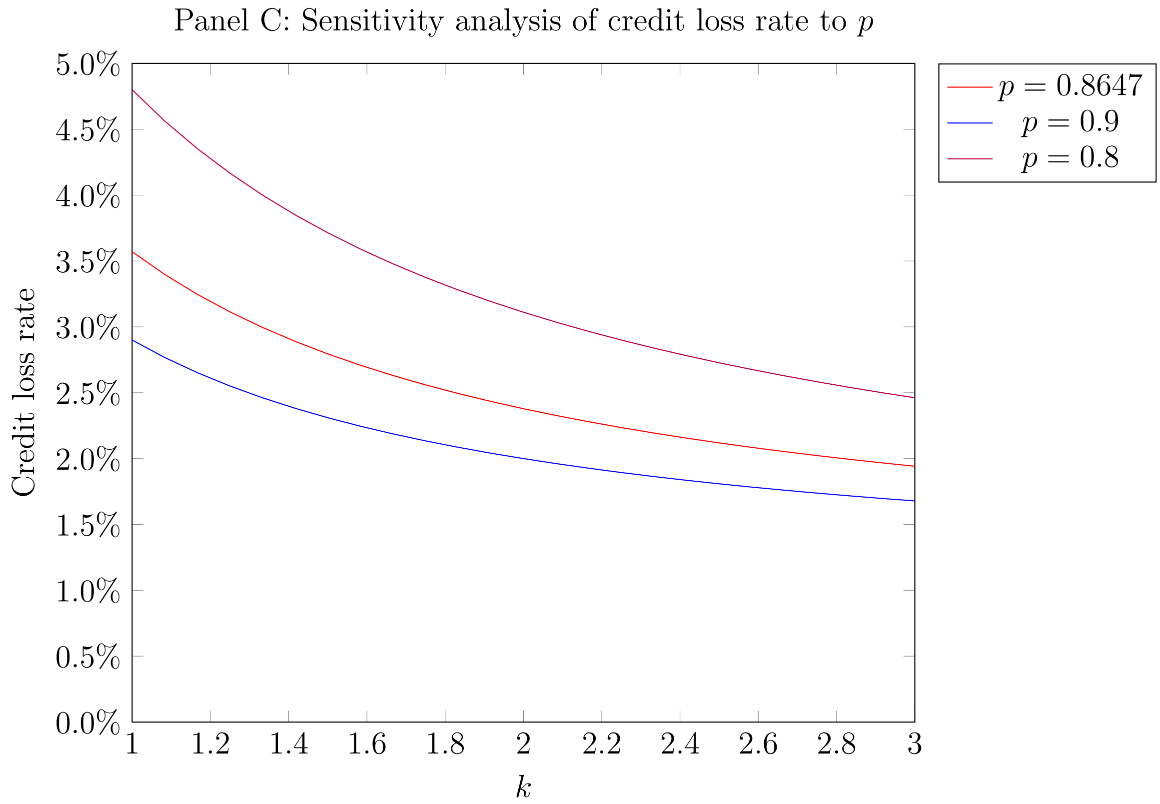


Figure 13: Sensitivity analysis of credit loss rate to k

Notes: This figure plots the sensitivity analysis of the aggregate Credit Loss Rate to changes in k. In each panel, we set the base case to $p = 84.67\%, c = 1.25\%, x = 1\%, y = 20\%$, represented by the red curve. Panel A, B and C show how the sensitivity of Credit Loss Rate to k responds to changes in x, y and p respectively. We omit the graph of how Credit Loss Rate reacts to changes in c because fixed costs to service each customers do not affect Credit Loss Rate.

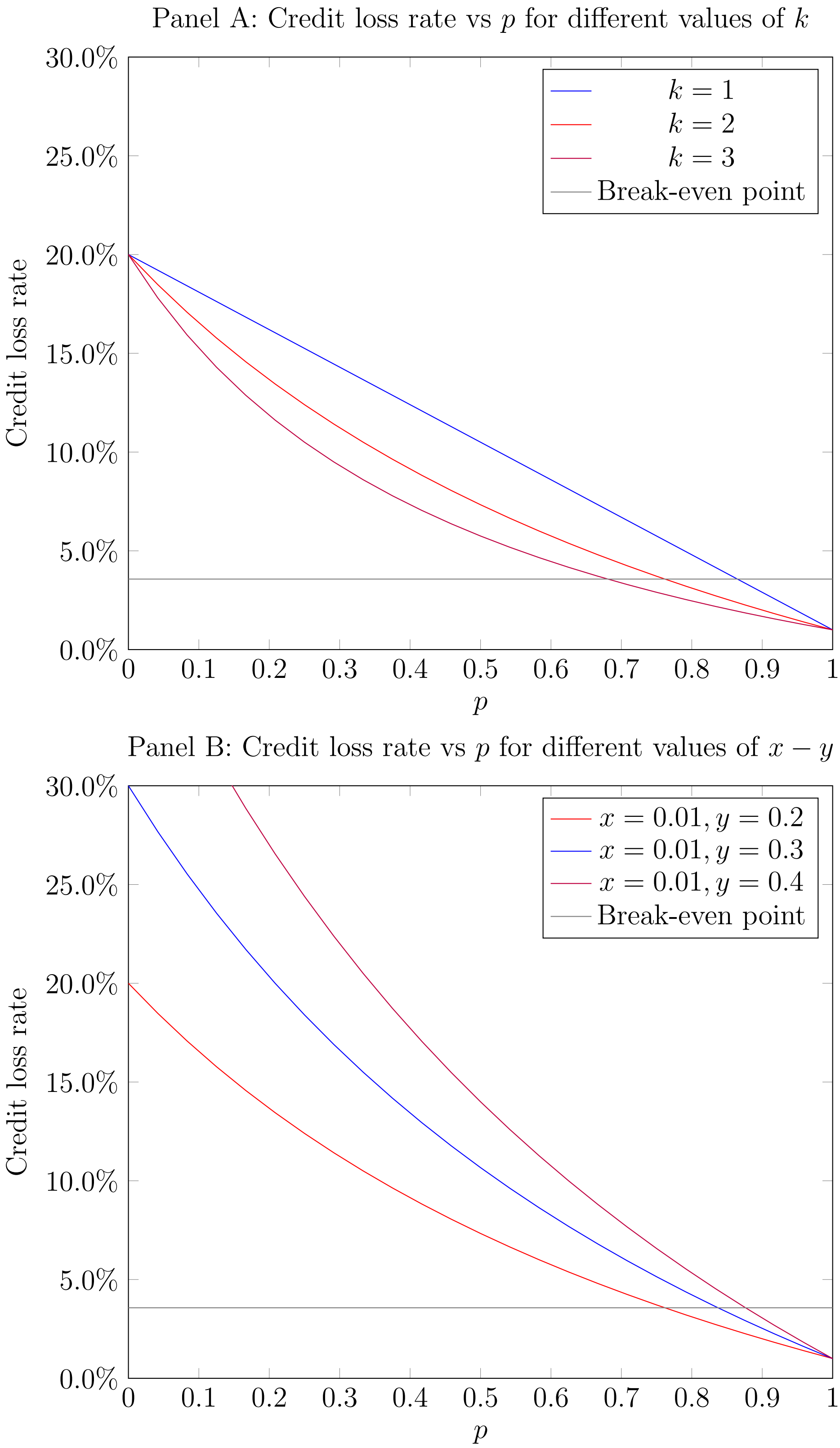


Figure 14: Sensitivity analysis of credit loss rate to p

Notes: This figure plots Credit Loss Rate against the proportion of loans lent to good customers (p). The default parameters are $k = 2$, $x = 1\%$, $y = 20\%$ and $c = 1.25\%$, represented by the red curve in each sub-figure. The break-even point represents the highest credit loss rate that the lenders can afford and still make a profit per loan. Portion of the curves below the break-even point indicates the values of p that lenders make a profit.

References

Agarwal, S., Skiba, P. M., and Tobacman, J. (2009). Payday Loans and Credit Cards: New Liquidity and Credit Scoring Puzzles? *American Economic Review*, 99:412–417.

Aguiar, M. and Hurst, E. (2013). Deconstructing life cycle expenditure. *Journal of Political Economy*, 121(3):437–492.

Ah Fook, L. and McNeill, L. (2020). Click to buy: The impact of retail credit on over-consumption in the online environment. *Sustainability*, 12(18).

Australian Bureau of Statistics (2022a). Employee Earnings and Hours, Australia.

Australian Bureau of Statistics (2022b). Household Impacts of COVID-19 Survey.

Australian Securities and Investment Commission (2020). Buy now pay later: An industry update. REP 672.

Ausubel, L. M. (1999). Adverse selection in the credit card market. Working paper.

Baker, T. H. and Kumar, S. (2018). The power of the salary link: assessing the benefits of employer-sponsored FinTech liquidity and credit solutions for low-wage working Americans and their employers. *M-RCBG Associate Working Paper Series*.

Barro, R. J. (1976). The loan market, collateral, and rates of interest. *Journal of Money, Credit and Banking*, 8(4):439–456.

Berg, T., Fuster, A., and Puri, M. (2021). Fintech lending. Working Paper 29421, National Bureau of Economic Research.

Bertrand, M. and Morse, A. (2011). Information disclosure, cognitive biases, and payday borrowing. *The Journal of Finance*, 66(6):1865–1893.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *The American Economic Review*, 75(4):850–855.

Boot, A. W. and Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, pages 899–920.

Boshoff, E., Grafton, D., Grant, A., and Watkins, J. (2022). Buy Now Pay Later: Multiple Accounts and the Credit System in Australia. Working paper.

Cao, Y. and Gruca, T. S. (2005). Reducing adverse selection through customer relationship management. *Journal of Marketing*, 69(4):219–229.

Carey, M., Prowse, S., Rea, J., and Udell, G. (1993). The economics of the private placement market. *Federal Reserve Bulletin*, 80:5.

Cooke, G. (2022). Australian credit card and debit card statistics. Technical report, Finder.

Cuffe, H. E. and Gibbs, C. G. (2017). The effect of payday lending restrictions on liquor sales. *Journal of Banking and Finance*, 85:132–145.

De La Rosa, W. and Tully, S. (2020). The impact of payment frequency on subjective wealth perceptions and discretionary spending. *Advances in Consumer Research Volume*, 48.

Diamond, D. W. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy*, 99(4):689–721.

Donner, H. and Siciliano, D. (2022). The impact of earned wage access on household liquidity and financial well-being. Working Paper, Stanford GSB.

Edmiston, K. (2011). Could restrictions on payday lending hurt consumers? *Economic Review*, 96:63–91.

Einav, L., Jenkins, M., and Levin, J. (2013). The impact of credit scoring on consumer lending. *RAND Journal of Economics*, 44(2):249–274.

Fuster, A., Hizmo, A., Lambie-Hanson, L., Vickery, J., and Willen, P. S. (2021). How Resilient Is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic. Working Paper 28843, National Bureau of Economic Research.

Fuster, A., Plosser, M., Schnabl, P., and Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies*, 32(5):1854–1899.

Gelman, M., Kariv, S., Shapiro, M. D., Silverman, D., and Tadelis, S. (2014). Harnessing naturally occurring data to measure the response of spending to income. *Science*, 345(6193):212–215.

Gerardi, K., Herkenhoff, K. F., Ohanian, L. E., and Willen, P. S. (2018). Can't Pay or Won't Pay? Unemployment, Negative Equity, and Strategic Default. *The Review of Financial Studies*, 31(3):1098–1131.

Gerrans, P., Baur, D. G., and Lavagna-Slater, S. (2022). Fintech and responsibility: Buy-now-pay-later arrangements. *Australian Journal of Management*, 47:474–502.

Guiso, L., Sapienza, P., and Zingales, L. (2013). The determinants of attitudes toward strategic default on mortgages. *The Journal of Finance*, 68:1473–1515.

Guttman-Kenney, B., Firth, C., and Gathergood, J. (2022). Buy Now, Pay Later (BNPL)...On Your Credit Card. Working Paper.

Hawkins, J. (2021). Earned wage access and the end of payday lending. *Boston University Law Review*, 101:705.

Hibbeln, M., Norden, L., Usselmann, P., and Gürtler, M. (2020). Informational synergies in consumer credit. *Journal of Financial Intermediation*, 44:1042–9573.

Holton, G. (2022). Unions join to give voice on job casualisation and COVID-19. https://search.informit.org/doi/epdf/10.3316/informit.393094127070563.

Jeong, S. (2021). Are wage advances the new payday loans? https://www.choice.com.au/money/credit-cards-and-loans/personal-loans/articles/are-wage-advances-the-new-payday-loans.

Kawai, K., Onishi, K., and Uetake, K. (2022). Signaling in online credit markets. *Journal of Political Economy*, 130(6):1585–1629.

Levy, R. and Sledge, J. (2012). A complex portrait: An examination of small-dollar credit consumers. *Center for Financial Services Innovation, Report*.

Liberman, A. (2016). The value of a good credit reputation: Evidence from credit card renegotiations. *Journal of Financial Economics*, 120:644–660.

Lowrey, A. (2013). Do millennials stand a chance in the real world. https://www.nytimes.com/2013/03/31/magazine/do-millennials-stand-a-chance-in-the-real-world.html.

Matuszyk, A., Mues, C., and Thomas, L. C. (2010). Modelling LGD for unsecured personal loans: Decision tree approach. *Journal of the Operational Research Society*, 61(3):393–398.

Meier, S. and Sprenger, C. D. (2015). Temporal stability of time preferences. *Review of Economics and Statistics*, 97(2):273–286.

Melzer, B. T. (2011). The Real Costs of Credit Access: Evidence from the Payday Lending Market. *Quarterly Journal of Economics*, 126:517–555.

Milde, H. and Riley, J. G. (1988). Signalling in credit market. *The Quarterly Journal of Economics*, 103(1):101–129.

Morgan, D. P., Strain, M. R., and Seblani, I. (2012). How payday credit access affects overdrafts and other outcomes. *Journal of Money, Credit and Banking*, 44(2-3):519–531.

Morse, A. (2011). Payday lenders: Heroes or villains? *Journal of Financial Economics*, 102:28–44.

Murillo, J., Vallee, B., and Yu, D. (2022). Fintech to the (Worker) Rescue: Earned Wage Access and Employee Retention. Working Paper.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2):147–175.

Nakamura, L. I. and Roszbach, K. (2018). Credit ratings, private information, and bank monitoring ability. *Journal of Financial Intermediation*, 36:58–73.

Ossip, D. (2020). It's time for companies to pay employees on-demand. *Harvard Business Review*.

Sier, J. (2022). Beforepay tanks 42pc on debut. *Australian Financial Review*.

Skiba, P. M. and Tobacman, J. (2019). Do Payday Loans Cause Bankruptcy? *Journal of Law and Economics*, 62:485–519.

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics*, 87(3):355–374.

Steijvers, T. and Voordeckers, W. (2009). Collateral and credit rationing: A review of recent empirical studies as a guide for future research. *Journal of Economic Surveys*, 23(5):924–946.

Stiglitz, J. E. (1975). The theory of screening, education, and the distribution of income. *The American Economic Review*, 65(3):283–300.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410.

Stiglitz, J. E. and Weiss, A. (1983). Incentive effects of terminations: Applications to the credit and labor markets. *The American Economic Review*, 73(5):912–927.

Tiruppatur, V., Chang, O., and Egan, J. (2010). ABS market insights: Understanding strategic defaults. *Morgan Stanley Research*.

Visa (2019). Earned wage access. Visa Insights.

Woolard, C. (2021). The Woolard Review - A review of change and innovation in the unsecured credit market. Technical report, Financial Conduct Authority.

Zaki, M. (2016). Access to short-term credit and consumption smoothing within the paycycle. *FEEM Working Paper*.

Zinman, J. (2010). Restricting consumer credit access: Household survey evidence on effects around the oregon rate cap. *Journal of Banking and Finance*, 34(3):546–556.