Consumer marketplace lending in Australia: credit scores and loan funding success

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Abstract

This paper examines borrower acceptance in consumer marketplace lending, using a unique dataset from the largest consumer lending marketplace platform in Australia, Society One. Our paper analyses the structure and determinants of loan funding on the platform. Applications are initially filtered through an automated decision tree based on a third-party credit score (Veda score). Subsequently, under the Responsible Lending regulatory requirements in Australia (ASIC 2014), loan applications are underwritten by the platform before being offered to sophisticated investors for purchase. We find that the growth in loan volume through the platform does not appear to be driven by a decline in lending standards. Augmenting credit decision models with both traditional and non-traditional underwriting variables helps explain funding outcomes. Applicants seeking loans for debt consolidation are more likely to be funded, while those from lower socioeconomic areas are less likely to both seek debt consolidation loans and be purchased by platform investors.

Keywords: marketplace lending, credit scoring, consumer lending, debt consolidation.

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Introduction

The emergence of online peer-to-peer and marketplace consumer lending providers over the past decade has facilitated access to credit to prospective household borrowers. Under a typical marketplace lending system, a platform acts as a conduit for lenders to provide funding to prospective borrowers. This paper aims to analyse the determinants of funding success on an Australian marketplace consumer lending platform, Society One, which requires applicants to submit to a manual underwriting process, as opposed to leaving the credit decision in the hands of the borrowers. We aim to determine the extent to which the manual underwriting process impacts credit provision, beyond information contained in borrower credit scores. As the platform is competing for high-credit customers against established financial institutions, while operating at an informational disadvantage in terms of a lack of credit information, we also aim to determine whether the growth of the platform is sustainable, insofar that lending standards are not declining. We argue that the underwriting process is valuable in explaining credit decisions of the platform, and demonstrate that the rate of applicant funding success, 11.68% on average, does not appear to be increasing over time. These results suggest it is possible for the platform to grow sustainably over time.

There have been several strands of research into marketplace lending over the past decade. Many of these studies have been based on observable loan applications and funded loans from platforms in the United States, such and Prosper.com and Lending Club, and to some extent on platforms in China and elsewhere. These studies have examined a range of issues, including: what determines loan funding success and loan performance (Sonenshein et al. 2011, Duarte et al. 2012, Lin et al. 2013, Gonzalez and Loureiro 2014, Emekter et al. 2015, Miller 2015, Iyer et al. 2016, Lin et al. 2016, Li et al. 2016, Netzer et al. 2016, Freedman and Jin 2017, Hertzberg et al. 2017, and Jagtiani and Lemiuex 2017), the behavioural dynamics of borrowers and lenders (Herzenstein et al. 2011, Zhang and Liu 2012, Mild 2015, and Paravisini et al. 2017), the role of auction-based and posted-price bidding mechanisms (Franks et al. 2016, Wei and Lin 2017), and the position of online lending marketplaces in relation to existing consumer credit markets (De Roure et al. 2016, Jagtiani and Lemiuex 2017, Liskovich and Shaton 2017, and Bertsch et al. 2017).

Our study also looks at the determinants of funding success, while departing from earlier studies several ways. First, this is the first study that we are aware of which examines the determinants of funding success in the Australian context. With the notable expectation of Murphy and Davis (2016), there has been no published academic study (of which we are aware) of marketplace lending in Australia. As such, this study sheds light on the industry, credit and regulatory situation of consumer marketplace lending outside of the United States and Europe. A key difference is that the Australian banking system is highly concentrated around the largest ‘big four’ banks (FSI 2014). Together the big four banks accounted 79 per cent of total domestic bank assets and 82.4 percent of total domestic household lending in Australia at the end of June 2017 (Authors estimates based on APRA 2017). There is a very high rate of bank penetration in Australia, with an estimated 97.7 per cent of people over 18 having a bank account (Connolly 2014). However, unsecured personal loan rates have remained relatively high, despite significant decline in bank funding costs over the past decade. Survey evidence estimates that 17.3 percent of adults in Australia stated that they were “just managing” or had debts “larger than their ability to repay” (Muir et al. 2016). Marketplace lending thus has the potential to compete against the oligopolistic banking sector by providing lower cost personal loans to borrowers, who may be able to benefit from refinancing or reducing the costs of their debt burden. This is as opposed to increasing financial inclusion to borrowers that are underserved by the status quo arrangements (e.g. Jagtiani and Lemiuex 2017). Under Australia’s extant negative credit reporting regime, the paucity of reliable consumer credit data and the relatively strict regulatory regime for consumer lending means the decision to accept loan applications has required a layer of manual underwriting by consumer marketplace lending platforms to assess borrower creditworthiness. As result, funding success for prospective borrowers on consumer lending marketplaces in Australia is largely determined by the lending platform, rather than by individual investors as is the case elsewhere.

Second, we examine a unique and previously unexamined consumer loan marketplace, Society One, which is the largest consumer loan platform by value of loans issued in Australia. The borrower application screening and loan funding decision process on the Society One marketplace differs in critical respects from that observed on Prosper.com and Lending Club, which have been the focus of several earlier studies. Although Society One also uses an automated credit decision tree, which declines prospective borrower applications under a minimum personal credit score, the second stage of the decision tree, which is whether to accept the loan onto the marketplace is subject to credit assessment by the platform’s loan officers. Thus, in addition to using automated credit risk screening processes, the platform *actively manages the credit decisioning process* by performing manual credit risk assessment in ways like a traditional bank lender, albeit with less internal credit data.

Third, this leads to differences in our dataset, which we discuss below. We observe all partially and fully completed consumer loan applications on the platform, as well as data on all loan applications accepted by the platform from when the platform commenced operations in August 2012 until August 2017. We observe individual loan applications across traditional credit scoring metrics, including third party credit scores for prospective borrowers, as well as information on age, occupation, employment status, income, and loan purpose. A novel feature of the data is the ability to determine how the borrower was directed to the platform (online). We classify a subset of borrowers as being linked from either ‘rate comparison’ or ‘credit check’ sites, which, respectively, allow borrowers to check potential rates available on personal loans, or enquire as to their likely availability of credit. Plausibly, these borrowers may be more financially literate or exhibit lower search costs in obtaining loans. Finally, we supplement our primary dataset by matching the postcode of all loan applicants with the Australian Bureau of Statistics’ Socio-Economic Index for Areas (SEIFA) (ABS 2013), to determine if additional information provided in local socioeconomic factors (or unobserved underwriting factors) also explains loan funding success.

We present a preview of the results as follows. Of prospective borrowers who complete their application, 11.68% are accepted by the platform, while 54.74% of applicants are rejected through the automated decision-tree and 33.68% are declined by the (manual) underwriting process. Successful applicants to the platform have higher Veda scores: 76.55% of loans are purchased from borrowers with Veda scores classified as “Good”, “Very Good,” or “Excellent,” with the lower bound for good set at a score of 622. In contrast, 38.59% of applicants who were declined by underwriters and 12.62% of applicants who were automatically declined exhibited Veda scores in this range. Borrowers with Veda scores in the “Below Average to Average Range,” and those with either negative scores (indicative of prior negative credit events) or zero scores (without credit history) are more likely than not rejected by automated decision tree (denied a quote). This supports the platform’s contention that they aim to provide funding to mainly prime borrowers.

The platform’s underwriting process contributes to loan acceptance on the platform through checking of bank accounts and document verification. We find that both occupation and employment status are predictors of loan acceptance on the platform. Full-time employees exhibit a funding rate of 15.81%, compared with 7.71% for part time or contract employees and 4.72% for those in seasonal employment. Applicants classified as “Professionals” or “Managers” are more likely to be funded (19.52% acceptance rate) than other applicants, including those working in trades, self-employed, or directors. Applicants who are not in paid employment or on government benefits are funded on less than 0.5% of occasions. Under the Responsible Lending requirements, borrowers should only be provided with funds if repayment appears likely (ASIC 2014). This presents prima facie evidence that borrowers are unlikely to be funded without the reliable capacity to repay the loan.

We present logistic regression models indicating that variables that may be utilised in the underwriting process. Variables relating to employment status, age, income, and loan to income ratio all exhibit significant coefficients in the expected direction when added as auxiliary variables to a model containing Veda scores. Incorporating these variables that we might expect to be used by underwriters shows that loans are more likely approved only after verification.

An applicant’s geographic location, in terms of socioeconomic advantage and disadvantage, as measured by the Australian Bureau of Statistics’ SEIFA index (ABS 2013), is strongly related to loan acceptance by Society One. Applicants from the lowest decile of socioeconomic areas in Australia exhibit an acceptance rate of 6.84%, compared to the acceptance rate of 16.87% for applicants in the highest socioeconomic decile. We demonstrate that applicants from higher socioeconomic deciles have higher Veda scores, are more likely to be employed full-time, and more likely to apply for personal loans for debt consolidation purposes, relative to applicants from lower socioeconomic deciles. For example, 8.25% of applicants in the top socioeconomic decile have Veda scores in the "Excellent" range, compared with 4.72% of applicants in the lowest decile. Debt consolidation is one of the core functions of the platform, with 45.07% of applications, and 53.12% of purchased loans seeking funding for this purpose. More than 50% of applicants in the top socioeconomic decile seek funding for debt consolidation, compared with 36.63% in the lowest decile, who are more likely than average to apply for vehicle financing. Nevertheless, the coefficient of the applicant's SEIFA decile is positive and significant in a logistic regression model containing Veda score information, employment status and loan purposes, suggesting that incremental information is available for underwriters by considering the relative prosperity of the applicant's geographic area. This is likely capturing both effects of local incomes and existing lines of credit.

In addition, there appears to be some forecasting power for loan acceptance based on the link to the platform's website. We identify applicants who visited the platform through two separate channels, rate comparison sites, which show borrowers the rates available on personal loans from a large selection of providers, and credit check sites, which allow borrowers to find out their Veda score and provides information regarding their creditworthiness with lenders. Applicants arriving at the platform through a rate comparison site are more likely than the average applicant to be funded, while those using credit check sites are less likely to be funded. In part, this reflects the higher average Veda score of those using rate comparison sites compared with credit check sites. It provides some evidence that people with lower search costs, who use the comparison sites, or those who are more financially literate in this case, are more likely to be funded. Alternatively, we find those who are uncertain about their capacity to obtain funds appear to be the most likely applicants to use credit check sites; the modal Veda range of applicants from comparison sites is [510, 621], or "Average" according to Veda.

Further, we find no evidence that loans are more likely to be accepted in later years of the platform's operations. Despite large growth in the number of loans funded on the platform, the acceptance rate on the platform has not significantly increased over time, controlling for other factors. Thus, we attribute the growth of the platform to increasing borrower awareness rather than declining lending standards.

1. Credit information in consumer lending marketplaces

In the most developed financial markets, like the United States and the United Kingdom, what started as peer-to-peer lending providers have undergone a transformation to become marketplace lending platforms. The first online peer-to-peer lending platforms, starting with Zopa in 2005 in the United Kingdom, followed by Prosper.com and Lending Club in 2006 the United States, and PaiPaiDai in China in 2007 allowed individual investors to invest in individual consumer loans. The terms marketplace lending and peer-to-peer lending are often used interchangeably, there are important difference as well as similarities in the underling financing models. Whereas *peer-to-peer lending* is characterised by financial contracting between 'peers', typically individual retail investors on one side and personal loan or small enterprise borrowers on the other in a loan marketplace, *marketplace lending* denotes the involvement of institutional investors on the funding side. In marketplace and peer-to-peer lending, the platform providers, charges a fee for service, usually to both the investor or borrower for screening, matching and administering the loan, but the stream of interest and principal repayments accrue to the investor rather than the platform. Loans tend to be unsecured loans, but may be secured for certain types of investors on some platforms. Platforms also tend to specialise in either consumer or business loans for SMEs, with the bulk of lending volume made up by consumer lending platforms. Consumer loan amounts vary but tend to be in the range of $1000 to $50,000. The loan contracts are usually short (1 year or less) to medium term loan contracts (3 and 5 years).

After experiencing an initial period of growth in the aftermath of the global financial crisis, the industry, particularly in the United States, subsequently underwent a transformation in scale in in the composition of funding sources (Lux and Chorzempa 2017). The Prosper.com and Lending Club marketplaces in the United States for instance, are now dominated by institutional rather than retail investor funding. Moreover, the predominant funding channels are arranged by packaging individuals loan contracts into Asset-Backed Securities (ABS) issuances which are bought by partner investment banks and asset management companies. The marketplace on the largest marketplace lending platforms in the United States has been transformed to a reliance on securitised packages of loan assets originated by platforms for sale to institutional investors. The price-setting mechanism for individual loan contracts has also evolved from auction-based to post-price setting for loans, and there is evidence that the loan pricing is partially determined by some measure of asset quality on the borrower side, and by prevailing macro-credit supply on the other (Bertsch, Hull, Zhang 2017).

A critical question in much of the empirical literature relates to how lenders or platform operators can evaluate available credit information from prospective borrowers. As a result, extant studies have utilised novel features of these markets as forms of field experiment. Certain features of the early Prosper lending marketplace in the United States between 2006 and 2008 provided the basis several studies of these questions. Notably, researchers were able to observe all listed loan applications from prospective borrowers, loan bids by investors in an auction-based loan price setting environment, funded loans and subsequent loan performance on the Prosper platform. Moreover, loan listings by prospective borrowers included a range of traditional and non-traditional credit information. Alongside traditional credit information, such as the prospective borrowers FICO credit score, loan amount and term sought, borrowers were also able to post a narrative description in support of their loan application and a profile photo of themselves. Borrowers and investors were also encouraged to connect with their peers and display and use online friendships in support of their loan applications or bidding strategies. In place of traditional credit risk assessment by bank credit officers, the credit decision process was left to non-expert peers.

A promise of online peer-to-peer lending is form of relationship lending in which ‘peer’ borrowers and lenders are assumed to have a low social distance, which is assumed to mitigate problems of asymmetric information leading to better credit quality and lower financing costs. Yet, the theoretical prediction of adverse selection (Akerlof 1970) as an information-type problem predicts adverse outcomes for markets under conditions of information asymmetry. The relationship between markets with imperfect information and credit rationing was also examined by Stiglitz and Weiss (1981) as a form of adverse selection problem. In the absence of perfect information about the quality of loan applications banks raise the interest rate to compensate for the risk of poor credit quality, with the potentially adverse effect of which is to exclude a section of borrowers from the market who may otherwise have the capacity and willingness to repay. The challenges of adverse selection under conditions of imperfect information, results in a higher cost of credit. Further, increased physical distance between borrowers and bank lenders, for example, has been found to lead to higher borrowing costs for customers who are more physically distant to bank lenders (Degryse and Ongena 2005). Relational distance, imperfect and asymmetric information problems can be assumed to be present in online marketplaces, with adverse implications for credit quality, investor behaviour and funding outcomes. Much of the empirical literature on online peer-to-peer lending which we discuss below has sought to evaluate these questions.

Based on observations from the Prosper marketplace several studies investigated the role of non-traditional or soft information as signals for borrower credit quality. Both the studies of Lin, Prabhala and Viswanathan (2013) and Freedman and Zhe (2017) showed that borrowers with strong social networks are more likely to obtain funding, and that funding is at a lower price than for other borrowers. However, the results were mixed as to whether the social ties fostered superior credit quality. Society One does not, however, use information from the social networks of applicants in making credit decisions, and rather than selecting loans on individual borrower profiles, investors funds are allocated by an auto-bidding system based on their allocation preferences.

Other papers in this vein look at the role of soft information in borrower-authored narratives in loan application listings on loan funding, pricing, and credit outcomes (Iyer, Khwaja, Luttmer, and Shue

2016, Sonenshein, Herzenstein, and Dholakia 2011, and Netzer, Lemaire, and Herzenstein, 2016). In this respect, our paper also contributes to the literature on risk analysis, specifically we contribute to the analysis of funding success in online lending marketplaces. Our setting differs from Emekter et al. (2015) and others on the literature on funding success (e.g., Lin et al. 2013, Iyer et al. 2016, and Freedman and Zhe 2017) in two main respects. Firstly, the platform underwrites loans before offering to lenders, rather than directly offering borrowers meeting the credit-score threshold to lenders. This additional layer may help to eliminate potential borrowers based on unverifiable or adverse information that is not reflected in credit scores. Secondly, lenders are either institutions or sophisticated individuals, and do not select specific loans for investment, but are allocated to fund fractions of loans in line with their stated risk preferences. Thus, soft information is used neither by borrowers or the platform underwriters.

2. Institutional Setting

The founding of comparable peer-to-peer and marketplace lending platforms in Australia came at much later point in the sector's international development, with the first new platforms in Australia offering their first loans in 2012 (Society One) and 2014 (Ratesetter, Australia). While alternative lending platforms started later in Australia, they were able to benefit directly and indirectly from the operational and underwriting experience of platforms in the US and UK to scale relatively quickly once established. There is also evidence of higher institutional involvement in platform ownership at the outset in Australia. Society One for instance counts among its institutional owners, Westpac Group's Reinventures Fund, i.e. the venture fund of one of Australia's 'big four' banks, along with media conglomerates and smaller local banks. At the time of writing Society One was Australia's largest consumer marketplace lending platform by the total value of loans issued, with over AUD $254 million in consumer loans issued from 2 August 2012 until 8 August 2017. Although the platform also offers secured business loans to agricultural borrowers, most of the platform's lending by value is to consumers. The average loan size issued to consumers on the platform during this period was $19272, and the median loan size was $16000. On the funding side the Society One marketplace is open only to wholesale investors, i.e. institutional and sophisticated (accredited) investors.

As with other countries internationally, online consumer market place lending in Australia has grown rapidly from a low base. From US$2.14 million in loan value reported in 2013, the cumulative equivalent of US$238.6 in marketplace consumer loans were made in Australia in the years from 2013 to 2016 (Garvey et al. 2017). Although the total value of loans funded is small compared to the value of unsecured personal bank lending in Australia, marketplace loans offer potentially fast access to cash loan at rates potentially lower than the equivalent bank rates. For instance, the average unsecured fixed term personal lending rate across Australian banks was above or just under 14% annual interest from 2013 to 2016 (RBA 2017). On the funding side, investors have also been attracted by the potential returns on marketplace loans, which are above the historically low cash rate or comparable term deposit rates in the decade since the global financial crisis.

The regulatory framework for consumer marketplace lending in Australia

Marketplace lending platform operators in Australia are regulated by the Australian Securities and Investments Commission (ASIC) based on requirements under the *Corporations Act 2001* (Corporations Act) (ASIC 2016). Platforms which offer marketplace lending products to wholesale investors generally have less stringent requirements than platforms which offer products to retail investors. ASIC sets forth regulatory guidance for marketplace lending operators, including the following Platform operators generally need to hold an Australian Financial Services Licence (AFSL) issued by ASIC. Under the current regime, platforms are generally structured as managed investment schemes. Marketplace lending platforms which are structured as managed investment schemes, and which offer products to retail investors are required to register the scheme with ASIC, whereas platforms with similar structures offering investment products to wholesale investors do not have to register the schemes.

In addition to the AFSL license and registration of retail investor facing schemes with ASIC, platforms which facilitate lending to consumers also need to hold an Australian Credit License (ACL) and to comply with the National Consumer Credit Protection Act 2009 (National Credit Act) and the Responsible Lending Requirements set out in Chapter 3 of the National Credit Act (ASIC 2016). The requirement of holding an Australian Credit Licence, prevents investors, whether wholesale or retail investors, from directly contracting loans with consumers. In this case, the credit provider is the platform or a custodian entity, which contracts the loans and holds the assets on behalf of investors in the managed investment scheme under which the platform is structured. Under the Responsible Lending Requirements for consumer lending, platforms and their custodians are required to understand the financial situation of particular consumers who are apply for loans on the platform, and verify loan information and the financial situation of the consumer along with assessing if the loan is suitable for the consumer.[1] The effect of the Responsible Lending requirement is that marketplace lending platform operators are actively involved in credit assessment to an extent they are not in other jurisdictions, such as the United States, where loan acceptance may be based on ID

[1] Marketplace lending platforms which are only engaged in business lending are not regulated under the National Credit Act, but do have to comply with the ASIC Act 2001, including “prohibitions on misleading or deceptive representations and use of harassment and coercion in recovering payments" (ASIC 2016).

and minimum FICO score cut-offs before being listed on the marketplace.

3. Data analysis

Our dataset is provided directly by Society One, and includes information on loan applications and approvals, as well as investor portfolios and their preferences. We focus on the loan applications in this paper and discuss the individual aspects of the data in more detail below. The period covered by the data is from August 2, 2012, when the platform commenced operations, until August 9, 2017.

Loan Applications

We obtained 250,276 fully- and partially-completed loan applications from Society One, an average of 4,103 applications per month over the 61-month period. The platform has experienced substantial growth in the volume of applications over the period studied. During the financial year July 2013 to June 2014, a total of 2,068 applications were made on the platform, this figure grew to 141,141 applications in the 2016/17 financial year. Monthly growth rate of applications has averaged 14.04% over the platform's life, as represented graphically on Figure 1.

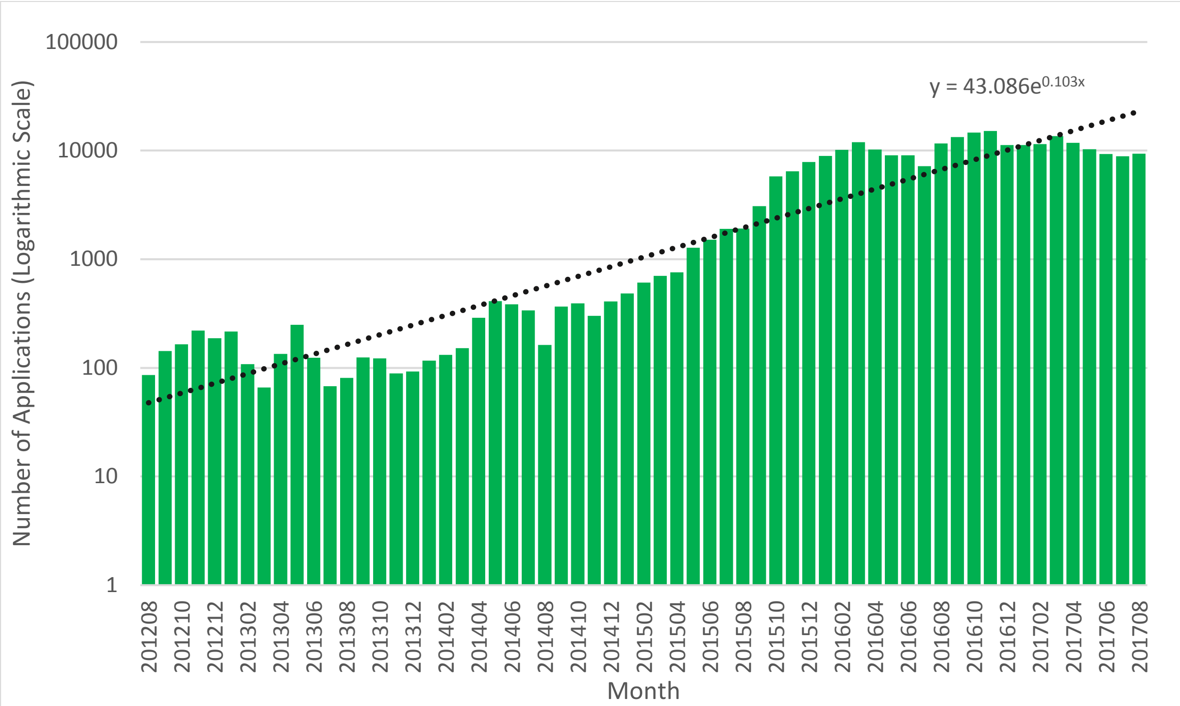

Figure 1: Monthly Number of Applications for Society One, August 2012 – August 2017. Logarithmic scale for y-axis.

Applicants to Society One are required to meet several criteria before being eligible to apply for a loan. These are clearly reported on the website, and include: Australian citizenship or permanent residency, age of 21 or above, employment income of more than $25,000 p.a., an ability to afford the loan, a minimum of two years of good credit history, no hardship, no bankruptcy (pending or previously) and that the loan is for an individual, not a business.

Each loan application made online through the Society One website is retained, providing applicants enter sufficient details to allow for a credit check. This requires the loan applicant to input details including date of birth, address, type of residence (mortgage, rental, boarding, freehold or living with parents), and tenure at their current address. Following verification with Veda, one of the major credit scoring bureaus in Australia, further information about applicants is acquired; it is from this we obtain most of the data we analyse.

The Application Status reports the ultimate outcome of the loan application. The status is broken into several different outcomes, a) Accepted, b) Declined, c) No Quote (Rejected) d) Cancelled, and e) In Process. Firstly, Society One may offer the borrower the loan through the platform investors, an outcome we refer to as Accepted. If the loan is not purchased, there are a few potential reasons. Unsuccessful but completed applications are divided into Declined, where the underwriter has decided the borrower is too risky for the loan platform, or No Quote (Rejected), where the automated decision tree in the application process rejects the applicant (usually based on credit history or employment status. Applications that were incomplete are categorised as Cancelled, where the borrower began but did not finish the form, or did not provide documentation to the platform, or In Process, where the loan outcome is yet to be decided.

The distribution of application outcomes by financial year is shown in Table 1. Overall, there is an acceptance rate of 5.27% among all applications started on the platform. However, more than half (53.07%) of platform participants commence but do not conclude their application; cancellation rates peaked at over 61% of applications in 2016/17. Cancellation of the application may be driven by an inability to obtain documentation to finalise the application, or an undesired personal initial quotation.

Table 1: Application Outcomes including cancellations by Financial Year. Loan outcomes are divided into "Declined" – where the applicant was rejected by human underwriting decision based on loan documents, "No Quote" – applicants were refused funding based on automated decision-tree rejection (inadequate credit score, employment status, or income), "Purchased" – where the loan was accepted by the platform and the borrower received funding, "In Process" – the borrower has not finalised their loan application (awaiting provision of documents), "Cancelled" – the applicant did not proceed with the loan application after initial quotation.

Financial Year	Declined	No Quote	Purchased	In Process	Cancelled	Grand Total
2012/13	770	44	120	0	768	1,702
(Proportion)	(45.24%)	(2.59%)	(7.05%)	(0.00%)	(45.12%)	(100.00%)
2013/14	947	51	224	0	846	2,068
(Proportion)	(45.79%)	(2.47%)	(10.83%)	(0.00%)	(40.91%)	(100.00%)
2014/15	4,589	244	533	0	1,961	7,327
(Proportion)	(62.63%)	(3.33%)	(7.27%)	(0.00%)	(26.76%)	(100.00%)
2015/16	15,508	27,676	3,998	1	39,248	86,431
(Proportion)	(17.94%)	(32.02%)	(4.63%)	(0.00%)	(45.41%)	(100.00%)
2016/17	14,784	31,825	7,692	338	86,502	141,141
(Proportion)	(10.47%)	(22.55%)	(5.45%)	(0.24%)	(61.29%)	(100.00%)
2017/18	1,307	1,948	615	4,249	3,488	11,607
(Proportion)	(11.26%)	(16.78%)	(5.30%)	(36.61%)	(30.05%)	(100.00%)

Total	37,905	61,788	13,182	4,588	132,813	250,276
(Proportion)	**(15.15%)**	**(24.69%)**	**(5.27%)**	**(1.83%)**	**(53.07%)**	**(100.00%)**

We now focus on the completed loan applications by financial year, as reported in Table 2. The proportion of completed applications that are accepted by SocietyOne is 11.68% over the life of the platform. This relatively small fraction represents the aim to only provide credit to highly creditworthy borrowers. Among loan applications that were declined, there is a clear change following the start of the 2015/16 financial year in the decision-making process. Prior to the 2015/16 financial year, fewer than 5% of completed applications were automatically rejected by the platform. However, this figure has grown substantially since the start of the 2015/16 financial year, resulting in over 50% of applications being denied due to the automatic decision-process. This reflects an increase in the platform's lending standards due to lender preferences; the Veda score threshold for borrowers to be automatically declined rose from 452 to 518.

The balance of the completed loan applications are those that were declined through the platform's underwriters. This process is more time-consuming and labour-intensive than the automated decline, and in part the growth of the platform has been driven by the changing decision-tree to automate loan processing. Under the ASIC regulation RG209, however, part of the underwriting process is to inquire and verify credit applicants' financial statements (ASIC 2014). Under the Responsible Lending obligations in the National Credit Act, the lender must ensure that the credit contract is 'not unsuitable' for the consumer (RG 209.2), including whether the borrower would be unable to meet their payment obligations (or only with substantial hardship).

Table 2: Outcomes for completed loan applications by financial year (July 1 – June 30). "Declined" indicates the loan was rejected through the manual underwriting process. "No Quote" indicates the applicant was rejected by the automated decision-tree. "Purchased" indicates the applicant was approved by the platform. "(Proportion)" states the percentage of applicants within a financial year in a particular loan outcome category.

Financial Year	Declined	No Quote	Purchased	Total
2012/13	770	44	120	934
(Proportion)	(82.44%)	(4.71%)	(12.85%)	(100.00%)
2013/14	947	51	224	1,222
(Proportion)	(77.50%)	(4.17%)	(18.33%)	(100.00%)
2014/15	4,589	244	533	5,366
(Proportion)	(85.52%)	(4.55%)	(9.93%)	(100.00%)
2015/16	15,508	27,676	3,998	47,182
(Proportion)	(32.87%)	(58.66%)	(8.47%)	(100.00%)
2016/17	14,784	31,825	7,692	54,301
(Proportion)	(27.23%)	(58.61%)	(14.17%)	(100.00%)
2017/18	1,307	1,948	615	3,870
(Proportion)	(33.77%)	(50.34%)	(15.89%)	(100.00%)
Total	**37,905**	**61,788**	**13,182**	**112,875**

Proportion	**(33.58%)**	**(54.74%)**	**(11.68%)**	**(100.00%)**

The Loan Applications data includes a unique loan application number and date that the loan application commenced. Demographic characteristics including Age, Postcode and Suburb, Occupation (Retail/Sales, Trade, Office Staff, Manager, Professional, Self-Employed, Student, Director, Beneficiary, or Other), and Income are added to the data. Applications also include the type of wage that is earned, falling into the categories of full-time, part-time, casual, contract, not in paid employment, unemployed, pension/government benefits, seasonal, and unemployed. While income is validated at the underwriting phase of the application, it is self-reported for those that cancel their application before this stage.

Applicants also state the Loan Purpose, which falls into the categories of (Debt Consolidation, Holiday/Wedding, Vehicle (Refinance or Purchase), Home Improvement, Education or Student Expenses, Major Purchase, or Other).[2] Loan purposes are self-reported; as loans are unsecured applicants are not required to deploy funds as designated in the application. However, part of the underwriting process involved in obtaining a loan is a document check. For instance, if an applicant is seeking finance to purchase a vehicle, the proposed purchase price of the vehicle is checked to ensure congruence with the loan amount. Conversely, in the case of a loan for debt consolidation, it is not possible to ensure that borrowers close their credit card account with the loan proceeds (or subsequently borrow additional funds).

Loan Outcomes by Amount Sought and Loan-to-Income Ratio

Prudent financial behaviour is required under the responsible lending guidelines set out by ASIC RG 209 regulations (ASIC 2014). Part of this would be indicated through the lending of money only to people with a reasonable expectation of being able to repay the loan. In Table 3 we report loan outcomes for completed applicants by amount sought, in bands of $10,000. Examining the distribution of applications, the largest proportion of applicants seek loans of under $10,000. Interestingly, this group also exhibits the lowest purchase rate (7.33%) and the highest rate of automated rejection (58.93%). Although fewer applicants seek larger amounts of funding, the acceptance rate is generally steady for loan amounts between $10,000 and $40,000, but increases markedly for loans above $40,000, to 22.72%. The low acceptance rates for small loans and high

[2] Society One has used various forms of classifications for their loan purposes. For example, "Debt Consolidation" has been clarified for customers as "Pay off credit cards or other loans." We have combined Holiday and Wedding, and Education and Student Expenses into single categories, while a small number of loans that were classified as "Loans to family and friends" and "Business Loans" were included in the "Other" category. Note that Society One no longer accepts loans for business purposes.

acceptance rates for large loans suggests that borrowers are aware (to some degree) of the size of loan they can service.

Table 3: Loan Outcomes by Amount Sought. The table reports the outcome of completed loan applications: Declined (by underwriter), No Quote (declined by decision tree) and Purchased, by bands of the dollar value of loan sought. The (Proportion) row indicates the percentage of applications within each band of amount sought for each loan outcome.

Amount Sought	Declined	No Quote	Purchased	Total
0-9,999	13,658	23,858	2,966	40,482
(Proportion)	(33.74%)	(58.93%)	(7.33%)	(100.00%)
10,000-19,999	10,652	14,724	4,059	29,435
(Proportion)	(36.19%)	(50.02%)	(13.79%)	(100.00%)
20,000-29,999	6,720	10,409	2,889	20,018
(Proportion)	(33.57%)	(52.00%)	(14.43%)	(100.00%)
30,000-39,999	5,907	11,007	2,457	19,371
(Proportion)	(30.49%)	(56.82%)	(12.68%)	(100.00%)
40,000+	968	1,790	811	3,569
(Proportion)	(27.12%)	(50.15%)	(22.72%)	(100.00%)
Total	**37,906**	**61,790**	**13,182**	**112,879**
(Proportion)	**(33.58%)**	**(54.74%)**	**(11.68%)**	**(100.00%)**

Table 4 reports loan outcomes by the loan amount sought to income ratio. This is more indicative of the loan-service capacity of the applicant than simply the loan sought. The ratio is grouped by bands of 10%, from below 10% of the borrower's income to above 50% of the borrower's income. For example, a borrower seeking a $10,000 loan with a $70,000 income would exhibit a ratio of 14.28%. Loan amounts to income ratio are presented in groupings of 10%; lower values indicate that the applicant should have greater capacity to service the loan. The most common ratio of amount sought to income is 10-20% with 24.35% of all applications falling into this range, closely followed by applicants seeking more than 50% of their income. The purchase rate is fairly steady for borrowers seeking a loan smaller than 30% of their annual income, and declines for ratios above this amount. Loan-to-income ratios therefore appear important in determining loan outcomes. For loan sizes above 50% of the borrower's income, the acceptance rate is only 4.83%, and rate of borrowers declined by the decision tree rises substantially above average to 68.32%. The capacity for borrowers to service loans is, unsurprisingly, a key factor the ability of applicants to obtain funding through the platform.

Table 4: Loan Outcomes for Completed Applications by Loan Amount Sought to Income Ratio. The table reports the outcome of completed loan applications: Declined (by underwriter), No Quote (declined by decision tree) and Purchased, by bands of the ratio of dollar value of loan sought to the borrower's reported annual income.

Loan To Income Ratio	Declined	No Quote	Purchased	Total
<10%	5,190	7,523	2,143	14,856
(Proportion)	(34.94%)	(50.64%)	(14.43%)	(100.00%)

10-20%	10,253	13,343	3,890	27,486
(Proportion)	(37.30%)	(48.54%)	(14.15%)	(100.00%)
20-30%	6,695	9,336	2,735	18,766
(Proportion)	(35.68%)	(49.75%)	(14.57%)	(100.00%)
30-40%	4,952	7,254	1,884	14,090
(Proportion)	(35.15%)	(51.48%)	(13.37%)	(100.00%)
40-50%	3,478	5,662	1,209	10,349
(Proportion)	(33.61%)	(54.71%)	(11.68%)	(100.00%)
>50%	7,337	18,670	1,321	27,328
(Proportion)	(26.85%)	(68.32%)	(4.83%)	(100.00%)
Total	**37,905**	**61,788**	**13,182**	**112,875**
(Proportion)	**(33.58%)**	**(54.74%)**	**(11.68%)**	**(100.00%)**

Loan Outcomes by Occupation and Employment Status

To assess the lending decisions by the platform, we examine the loan decisions by occupation and employment status. Occupation is generally self-reported, although confirmed later at the underwriting stage of the loan process. Table 5 Panel A reports loan outcomes by occupation. Applicants stating their occupation as "Professional" or "Manager" appear more likely to have their loan application approved, with a purchase rate of 19.52 per cent, relative to the unconditional purchase rate of 11.68%. By way of contrast, self-employed individuals are much less likely to have their loan accepted, with an acceptance rate of only 3.89%. A large fraction (48.1%) of the sample reports their occupation as "Other" or "Office Staff" and these applicants have an acceptance rate that is slightly below average at 9.67%. Those applicants classing themselves as students or beneficiaries are almost entirely excluded from the platform, with a 0.47% purchase rate and a 72.30% rate of automated decision-tree rejection. On the face of it, acceptance rates appear to conform to responsible lending when regarding occupation.

Table 5: Loan Outcomes by Occupation and Employment Status. Panel A reports loan outcomes by reported occupation: Declined (by underwriter), No Quote (declined by decision tree) and Purchased. Panel B reports loan outcomes by employment status (frequency with which the applicant works, as reported by the applicant but verified by platform).

Panel A: Occupation	**Declined**	**No Quote**	**Purchased**	**Total**	**Purchase Rate**
Professional/Manager	10,519	13,550	5,837	29,906	19.52%
Office Staff/Sales and Retail /Other	18,457	30,535	5,247	54,239	9.67%
Trade	4,846	8,276	1,510	14,632	10.32%
Self-Employed	2,066	4,896	282	7,244	3.89%
Director	711	1,121	275	2,107	13.05%
Beneficiary/Student	1,299	3,409	22	4,730	0.47%
Unknown	7	1	9	17	52.94%
Total	**37,905**	**61,788**	**13,182**	**112,875**	**11.68%**
Panel B: Employment Status					

Full Time	25,586	35,771	11,521	72,878	15.81%
Part Time/Contract	5,237	8,548	1,151	14,936	7.71%
Casual/Seasonal (Irregular Work)	3,443	5,776	457	9,676	4.72%
Benefits/Not in Paid Employment	3,628	11,690	39	15,357	0.25%
Not Stated	11	3	14	28	50.00%
Total	**37,905**	**61,788**	**13,182**	**112,875**	**11.68%**

Table 5, Panel B reports the loan outcomes by employment status. Of the 112,875 completed applications, 72,878 (64.57%) are from applicants with full-time employment. While the acceptance rate averages 11.68% for all completed loan applications, this proportion rises to 15.81% conditional upon the applicant being in full time employment. The next most common type of employment is part-time and contract, which comprises 14,936 of the total number of applicants, and yields an acceptance rate of 7.71%. Casual employees (4.94% acceptance rate) provide most of the remainder of loan acceptances. Clearly, the more permanent the employment type, the more likely the loan is to be accepted; the platform accepts less than 0.5% of the loans from seasonal employees, those on government benefits, or those without paid employment.

Loan Outcomes by Veda Score Range

For applicants who successfully complete enough of the application form a Veda score is obtained. Veda scores, like the US FICO scores, are numerical indicators of an individual's credit reputation. Veda (also known as Equifax) is one of three major 'third-party' credit bureaus in Australia, the others being Dun and Bradstreet (Illion) and Experian. However, Australia operates under a negative credit reporting regime and information about the creditworthiness of borrowers is only available based on credit applications, repayment history (adverse events), open credit lines, and personal history,[3] supplemented with public information from court records or ASIC records. Veda scores are not based on gender, race, dependents, salary or asset holdings due to the Privacy Act. The three credit providers base their credit scores on somewhat different information and there may be discrepancies over the level of information based on which institutions provide customer details to the credit bureaus. For example, a particular credit issuer such as bank or telco may only report applications to one of the credit bureaus, and this would be unknown to the other two.

According to Veda, scores typically fall into the range of 0 – 1200, where a higher credit score indicates a superior credit reputation. Individuals without a credit history (for example, never having held a post-paid mobile phone contract or a utility bill in their name) will have a credit score of 0.

[3] The exact formula used to calculate the score is proprietary. According to Veda, the formula weighs 51% of the score on credit applications and 30% of the score on repayment history. Which exact credit providers share their information with Veda is not publicly known.

Some individuals in the data set hold a negative credit score, indicative of prior adverse credit events, and applications that do not reach the underwriting phase of the application may not have their credit score reported in the data. Veda notes that personal loan issuers are likely to rely mainly on the credit score (rather than accompanying credit report) when making lending decisions. We are not aware of any prior studies that have used the Veda score to assess personal loan issuance in Australia.

Table 6: Loan Outcomes for Completed Applications by Veda Score. Veda scores are broken into seven bands; 1. Negative, 2. Zero. 3. (0, 509] - Below Average to Average. 4. [510-621] - Average. 5. [622,725] – Good. 6. [726,832] - Very Good. 7. [833,1,200) – Excellent. Cutoffs between bands and band descriptor (e.g. Average) are as described by Veda. The table reports the outcome of completed loan applications: Declined (by underwriter), No Quote (declined by decision tree) and Purchased, by the seven categories of Veda score.

Veda Score Range	**Declined**	**No Quote**	**Purchased**	**Total**
Negative	291	2,470	2	**2,763**
(Proportion of Category)	(10.53%)	(89.40%)	(0.07%)	**(100.00%)**
Zero	2,563	22,521	22	**25,106**
(Proportion of Category)	(10.21%)	(89.70%)	(0.09%)	**(100.00%)**
(0,509] – (Below Average – Average)	11,901	22,910	761	**35,572**
(Proportion of Category)	(33.46%)	(64.40%)	(2.14%)	**(100.00%)**
[510,621] – (Average)	8,524	6,091	2,306	**16,921**
(Proportion of Category)	(50.38%)	(36.00%)	(13.63%)	**(100.00%)**
[622,725] – (Good)	7,473	3,239	4,100	**14,812**
(Proportion of Category)	(50.45%)	(21.87%)	(27.68%)	**(100.00%)**
[726,832] – (Very Good)	4,389	2,363	3,476	**10,228**
(Proportion of Category)	(42.91%)	(23.10%)	(33.99%)	**(100.00%)**
[833, 1,200) – (Excellent)	2,764	2,194	2,515	**7,473**
(Proportion of Category)	(36.99%)	(29.36%)	(33.65%)	**(100.00%)**
Total	**37,905**	**61,788**	**13,182**	**112,875**
(Proportion)	**(33.58%)**	**(54.74%)**	**(11.68%)**	**(100.00%)**

Table 6 reports loan application outcomes for completed applications by ranges of Veda score (credit score). Credit scores typically take the range of 1 – 1000 in this data set, with blank (zero) values indicating a lack of credit history, and negative values indicative of adverse prior events in an applicant's credit history. We use the publically reported Veda score bands as cut-offs, which Veda determines as indications of applicant quality (e.g. https://www.finder.com.au/vedascore). An applicant in the range (0,509] is classified as "Below Average to Average," indicating a position in the bottom 20% of Veda's credit-active population. The four other positive categories of Veda score represent the higher four quintiles of the population. These are stated as [510, 621] – Average; [622, 725] – Good; [726, 832] – Very good; and [833, 1,200) – Excellent. A borrower may use a credit information site (credit check site) to find their credit score, presumably based on their classification they may expect to be able or unable to obtain credit from a loan provider.

From Table 6, most applicants had a credit record that could be retrieved (25,106 of 112,875 (22.24%) of applicants had a credit score that was blank). Veda score is a strong predictor of loan application success; applicants with superior credit history are far more likely to have their loan accepted on the platform. Nearly all successful applicants (94.04%) exhibited Veda scores above 509, and 33.84% of applicants with Veda scores above 725 had their loan accepted on the platform (compared to the unconditional acceptance rate of 11.68%). Very few applicants are accepted on the platform without an existing Veda score, or with a poor credit history.

We can also glean from the table that Veda score is an important determinant in the automated decision tree. Those applicants with negative, blank or Veda scores of less than 510 are significantly more likely than the average applicant to be declined without an interest rate quote. Rejected applicants with higher credit scores (510+) are more likely to be declined by the underwriter than the automated decision tree. The exact threshold for automated denial by the platform is time-varying, fluctuating with the risk appetite of the platform investors and the platform's ability to underwrite loans across the risk spectrum.

Table 7 reports rates of loan purchase by the socioeconomic area of the loan applicant. The Australian Bureau of Statistics (ABS) collects census data on socioeconomic advantage and disadvantage, known also as the Socioeconomic Index for Areas (SEIFA) index, at the postcode level for most localities in Australia. The ABS ranks postcodes into deciles based on population, from lowest-level socioeconomic conditions (decile 1) to highest level (decile 10).

Table 7: Purchase Rates for loans by Socioeconomic Advantage and Disadvantage decile of loan applicant. The table reports the number of applicants whose loan was declined, denied a quote (No Quote) or Purchased, conditional on the loan applicant's socioeconomic area, where the SEIFA index is matched at the postcode level to that of the loan applicant. Higher values of the index decile indicate that the applicant was from a postcode with a higher socioeconomic status. The column Purchase Rate indicates the proportion of loans applications within a SEIFA decile that were purchased by the platform.

SEIFA Decile	Declined	No Quote	Purchased	Total	Purchase Rate
1	3,120	6,040	673	9,833	6.84%
2	3,104	6,059	803	9,966	8.06%
3	2,768	5,252	837	8,857	9.45%
4	3,870	6,955	1,194	12,019	9.93%
5	3,623	6,160	1,251	11,034	11.34%
6	4,576	7,294	1,541	13,411	11.49%
7	4,060	6,505	1,485	12,050	12.32%
8	3,873	5,917	1,507	11,297	13.34%
9	5,057	6,764	2,124	13,945	15.23%
10	3,847	4,839	1,763	10,449	16.87%
Overall	37,898	61,785	13,178	112,861	11.68%

The rate at which loan applications are purchased increases monotonically with the SEIFA decile. Applicants from lowest SEIFA decile have purchase rate of 6.84%, compared to those in SEIFA decile 10 of 16.87%. Potential explanations may be that lower socioeconomic areas may coincide with lower Veda scores, or that they may coincide with other localised factors, such as lower incomes, more open credit lines relative to income, or less secure employment, may contribute to the ability to obtain a personal loan.

Applicants are relatively evenly divided across all 10 deciles, although platform use appears highest among the middle to higher SEIFA deciles. A lack of awareness of the platform does not appear to be a strong factor in an applicant's potential capacity to obtain a loan.

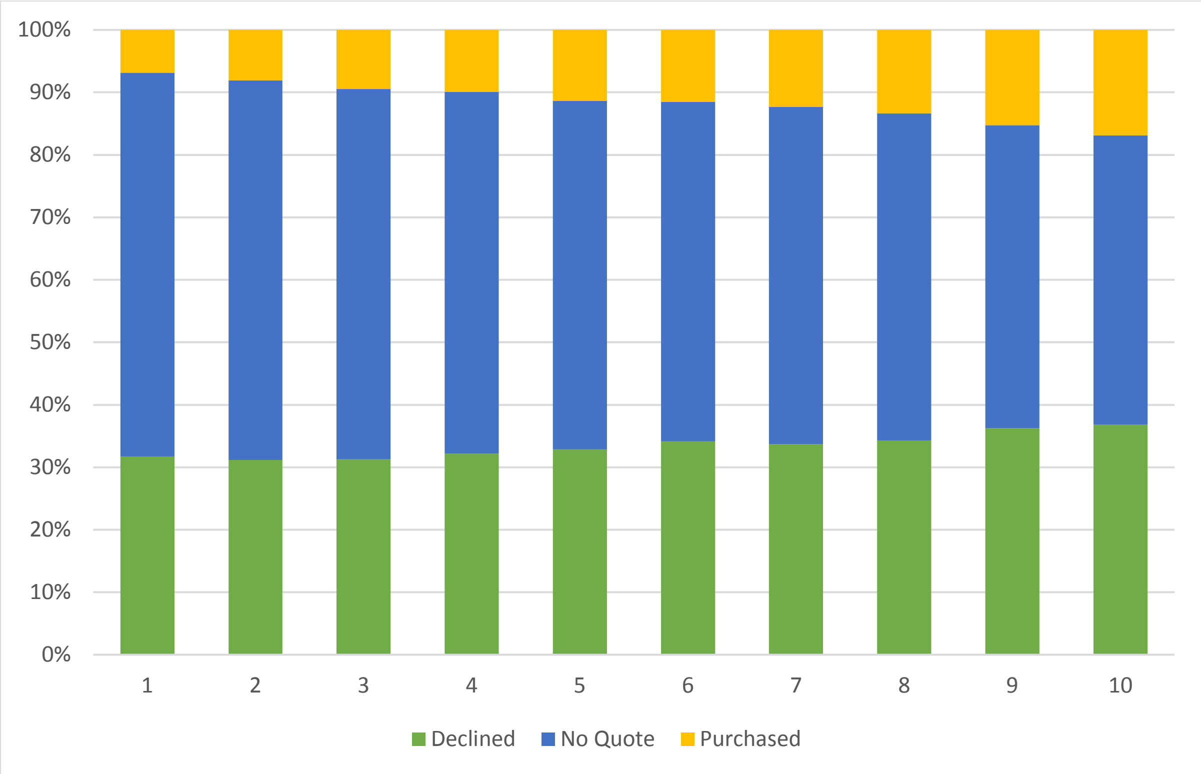

Figure 2: Purchase, Decline, and No Quote Rates by Decile of Socioeconomic Index for Areas (1 = Lowest Decile of Socioeconomic Advantage and Disadvantage, 10 = Highest Decile of Socioeconomic Advantage and Disadvantage).

Figure 2 presents the applications "declined" by underwriter, "no quote", and "purchased" rates for loans on the platform by SEIFA decile in a stacked bar chart (proportions add to 100%). As the SEIFA deciles increase, purchase rates increase and the proportion of applicants denied by underwriter rather than decision tree also increases, suggesting improved credit scores for those in higher socioeconomic areas.

Table 8 investigates further whether the Veda score is related to the decile of the SEIFA index. Here, Veda scores of applicants are broken into the ranges as in Table 6. As a proportion of all platform applicants falling into decile 1, for example, 4.73% exhibit Veda scores in the "Excellent" [833,1200) range. This proportion increases with the SEIFA deciles for the three highest Veda score ranges, suggesting that there is indeed a positive correlation between Veda score and localised socioeconomic conditions. Moreover, it is quite clear from Table 8 that applicants from lower socioeconomic deciles are more likely to have Veda scores in the "Below Average to Average" range of (0,509]. Applicants with negative or zero Veda scores are relatively evenly dispersed across the deciles, indicating that a lack of credit history or prior defaults on the credit record are relatively idiosyncratic events. Figure 3 presents the proportions graphically, only for those applicants with Veda scores above zero. It is evident that the proportion of potential lenders with the lowest positive Veda score band (0,509] declines as the SEIFA index increases. Thus there would appear to be a positive correlation between Veda score and the SEIFA index, although Veda score is based purely around an individual's credit history and not local socioeconomic factors.

Table 8: Proportion of applicants within Veda Score Ranges by SEIFA deciles. The table reports the proportion of loan applicants by socioeconomic decile (SEIFA) decile, where 1 indicates the lowest decile of the population by socioeconomic status and 10 indicates the highest decile. The 7 categories for Veda score range are as per the cutoffs defined by Veda described in the caption Table 6, with a higher Veda score indicative of better credit history. The Total row indicates the proportion of the population exhibiting a Veda score within a particular range.

	Proportion of Applicants in SEIFA Decile within Veda Score Range						
SEIFA Decile	Negative	Zero	(0,509]	[510,621]	[622,725]	[726,832]	[833,1200)
1	2.58%	22.18%	39.39%	14.60%	10.05%	6.47%	4.73%
2	3.10%	23.08%	34.48%	13.82%	11.43%	8.06%	6.04%
3	2.68%	22.59%	33.63%	14.86%	11.86%	8.07%	6.31%
4	2.69%	22.12%	33.87%	14.72%	11.71%	8.54%	6.36%
5	2.37%	22.30%	32.40%	14.80%	12.49%	8.90%	6.73%
6	2.35%	22.51%	31.25%	15.23%	13.36%	8.81%	6.49%
7	2.51%	22.65%	30.33%	15.34%	13.57%	9.17%	6.42%
8	2.47%	22.20%	28.49%	15.30%	14.00%	10.06%	7.48%
9	2.16%	21.60%	27.67%	15.57%	15.02%	10.89%	7.09%
10	1.72%	21.37%	25.96%	15.27%	16.70%	10.72%	8.25%
Total	**2.45%**	**22.24%**	**31.52%**	**14.99%**	**13.12%**	**9.06%**	**6.62%**

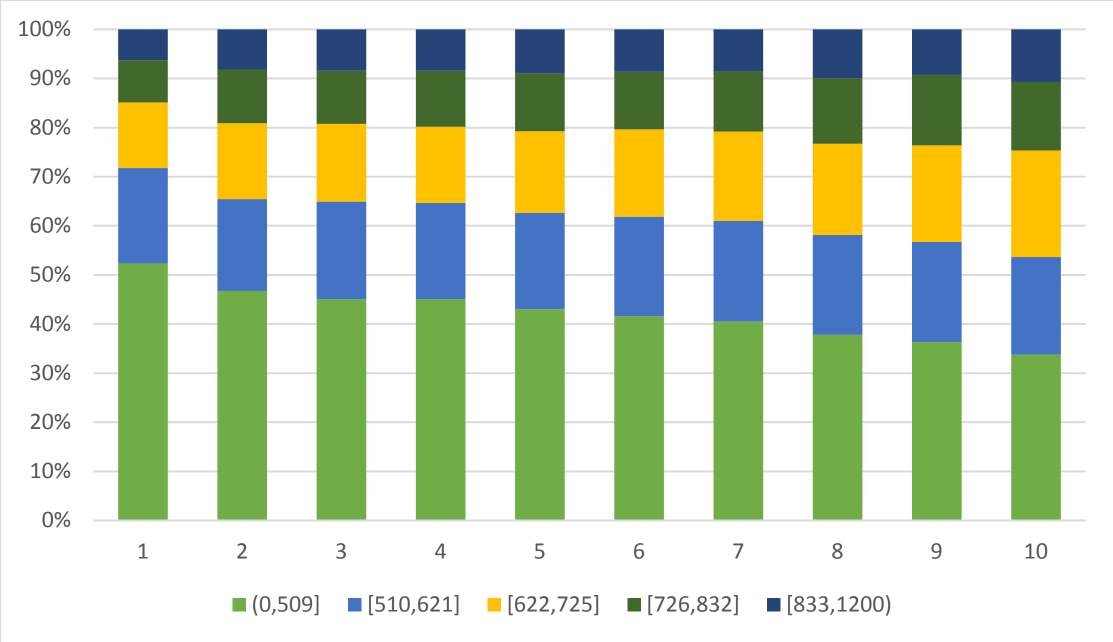

Figure 3: Proportion of loan applicants within each Veda score band, conditional on exhibiting a positive score, by decile of the SEIFA index (1=lowest socioeconomic area, 10=highest socioeconomic area).

Table 9 reports the employment status of loan applicants on the platform. As expected, in the lower socioeconomic deciles, applicants are less likely to be working full-time (56.43% of applicants work full time in the lowest SEIFA decile, compared with 76.43% in the highest SEIFA decile) and far more likely to be on benefits or not in paid employment (21.96% and 6.00% for the lowest and highest deciles, respectively). Combined with the evidence from Table 7 and Table 8, this suggests that there are important characteristics for loan applicants captured in the SEIFA index, relating to both personal credit history and employment status. It is of interest as to whether there is incremental information in predicting loan purchase rates based on the socioeconomic index for areas.

Table 9: Employment Status by SEIFA decile for loan applicants.

SEIFA Decile	Full Time	Part Time/Contract	Casual / Seasonal (Irregular Work)	Benefits / Not in Paid Employment
1	56.43%	11.88%	9.73%	21.96%
2	54.47%	13.81%	10.49%	21.22%
3	55.32%	14.45%	10.50%	19.68%
4	61.06%	12.81%	9.97%	16.15%
5	61.52%	14.16%	9.44%	14.85%
6	66.01%	13.55%	8.33%	12.12%
7	67.48%	13.07%	8.24%	11.17%
8	67.72%	13.97%	7.95%	10.34%
9	73.48%	12.86%	6.48%	7.13%
10	76.43%	11.92%	5.63%	6.00%
Overall	**64.57%**	**13.23%**	**8.57%**	**13.61%**

Table 10: Proportion of applications and loans purchased for specific loan purposes by socioeconomic index decile. Panel A of the table reports the proportion of applicants seeking a loan for by loan purpose within socioeconomic index bands (1 = lowest, 10 = highest). Panel B of the table reports the proportion of purchased loans with stated purpose within socioeconomic index bands.

Panel A: Loan Applications

SEIFA Decile	Debt Consolidation	Auto Loan	Holiday/ Wedding	Home Improvement	Other
1	36.63%	19.86%	14.11%	8.78%	20.62%
2	40.06%	20.21%	12.14%	7.97%	19.63%
3	42.12%	19.51%	10.84%	7.78%	19.75%
4	42.87%	17.98%	11.82%	8.73%	18.60%
5	45.45%	17.43%	10.92%	8.13%	18.07%
6	45.49%	16.94%	11.57%	7.64%	18.37%
7	46.88%	15.93%	11.83%	7.63%	17.73%
8	48.02%	16.01%	10.86%	8.01%	17.09%
9	49.33%	14.18%	11.20%	7.71%	17.58%
10	50.92%	12.61%	11.78%	7.70%	16.98%
Overall	**45.07%**	**16.90%**	**11.68%**	**7.99%**	**18.36%**

Panel B: Purchased Loans

	Debt Consolidation	Auto Loan	Holiday/ Wedding	Home Improvement	Other
1	47.40%	11.59%	15.16%	11.00%	14.86%
2	47.45%	13.70%	11.21%	11.08%	16.56%
3	50.78%	10.75%	10.27%	12.90%	15.29%
4	50.08%	10.30%	13.90%	12.23%	13.48%
5	52.92%	9.59%	10.79%	12.39%	14.31%
6	54.90%	10.71%	12.39%	8.83%	13.17%
7	54.28%	9.90%	11.72%	10.91%	13.20%
8	53.35%	11.28%	11.48%	11.61%	12.28%
9	55.84%	8.62%	11.06%	11.02%	13.47%
10	55.19%	8.45%	13.22%	9.36%	13.78%
Overall	**53.12%**	**10.13%**	**12.03%**	**10.96%**	**13.77%**

It is of interest to see whether stated loan purposes vary with the SEIFA index. Table 10 presents the proportion of applicants and purchased loans within each SEIFA decile by major categories of loan purpose. Panel A of Table 10 reports the proportion of applicants within each SEIFA decile seeking loans by purpose. Individuals in lower socioeconomic deciles tend to apply for automotive loans (both to purchase and refinance vehicles) in a higher proportion than those in the higher socioeconomic areas; 12.61% of applicants from the highest socioeconomic area were seeking loans for vehicles, relative to around 20% of applicants in each of the lowest two deciles. In contrast, there is a far greater tendency for people in higher socioeconomic areas to apply for personal loans for the purpose of debt consolidation; more than half of all applicants across the top two SEIFA deciles applied for debt consolidation loans, compared with only 36.63% in the lowest SEIFA decile.

Panel B of Table 10 reports the distribution of purchased loans (rather than applications) across deciles of the socioeconomic index by loan purpose. The differences between Panel A and Panel B provide some insight into the successful applicants within SEIFA deciles. Applicants for debt consolidation make up 45.07% of all loan applications, but 53.12% of all purchased loans. In all deciles of the SEIFA index, the proportion of purchased loans for debt consolidation purposes is higher than the proportion of applicants. The difference is particularly pronounced at the lower end of the SEIFA index; 36.63% of loan applicants in the decile 1 applied for a debt consolidation loan, whereas the proportion of accepted loans was 47.40% for debt consolidation purposes. The proportion of loans for debt consolidation purposes remains higher for applicants from higher socioeconomic areas. Loans for home improvement purposes are also more likely to be purchased than the rate of applications. The difference in purchase rates by loan purposes is offset by automotive loans; a far lower proportion of automotive loans are purchased on the platform (10.13%) than the proportion of overall applications (16.90%).

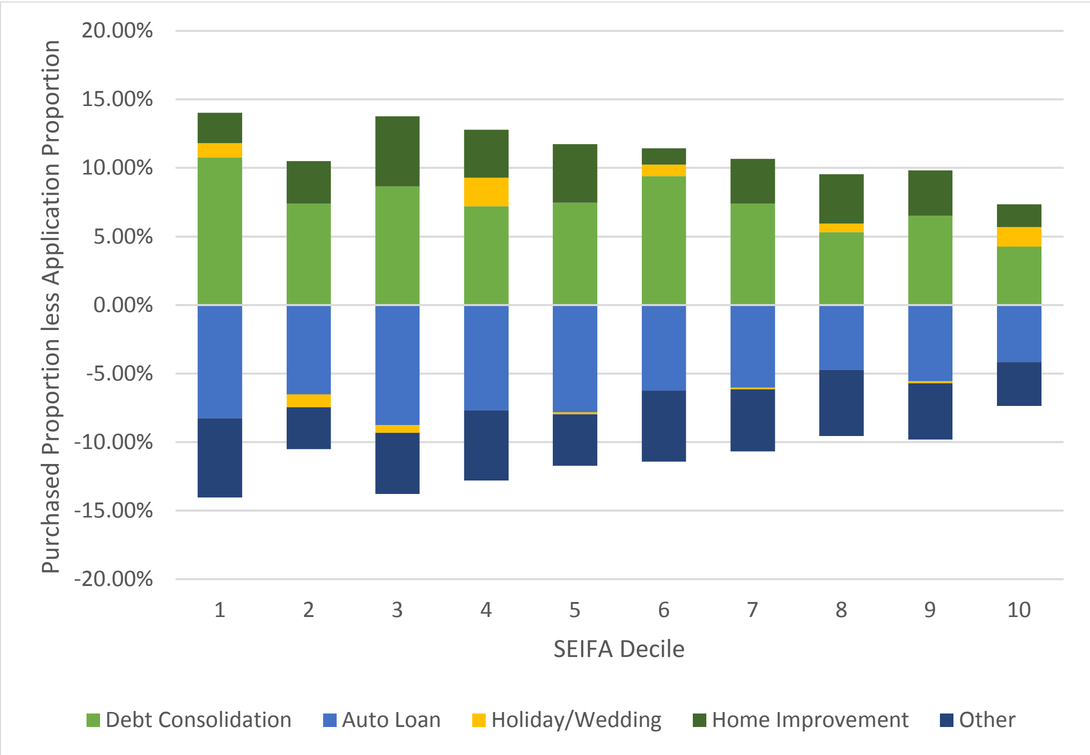

Figure 4: Purchased Proportions less Application Proportion by SEIFA Decile for Stated Loan Purposes.

Figure 4 shows the difference between purchased proportions and application proportions of each loan purpose by SEIFA decile. In each of the 10 deciles, debt consolidation and home improvement are larger fractions of the purchased loans than the loan applications, while automotive loans and those in "other" categories (without stated purpose) were less likely to be accepted. The difference in acceptances rates and application rates is most pronounced in lower deciles, particularly among applicants seeking to consolidate debt. Possible explanations are that those in lower socioeconomic areas are in more need of a vehicle (low socioeconomic areas tend to be outer suburban or rural areas in Australia), or perhaps are more in need of finance to purchase a vehicle compared to those in higher socioeconomic areas. On the other hand, applications for debt consolidation may be a function of financial literacy, which is likely higher in the regions with greater economic advantages.

Applications from Rate Comparison and Credit Check Sites

Table 11 reports the statistics for loan applicants by channel to the platform website. Data were collected by the platform using browser cookies, and refer only to the site from which the applicant immediately clicked through to the platform. We classify two types of website, Rate Comparison Sites and Credit Check Sites, with the balance of applicants arriving through other means, including search engine, banner advertisement, or by direct input into the address bar. Rate Comparison sites serve the main purpose of allowing potential borrowers to compare loan rates across different platforms, including banks, credit unions, and marketplace lenders. We are able to identify sites *Finder, Mozo, RateCity, CreditSimple* and *InfoChoice* as examples of this. Anecdotal evidence suggests that borrowers utilising these sites are more likely to be informed or discern loan providers based on price. Credit Check Sites allow borrowers to check their Veda score, and provide them with an indication of their likely capacity to obtain a loan. The Credit Check site we identify is *GetCreditScore*. Liskovich and Shaton (2017) find that borrowers value the ability to learn about their cost of credit; less informed borrowers may discover their relatively low credit scores and be surprised to find their application is rejected, with the use of such information sites a low-cost way of obtaining this information.

Panel A of Table 11 shows the usage of Rate Comparison Sites and Credit Check Sites for all applicants for major categories of loan purpose. Overall, 9.63% of applicants use Rate Comparison Sites when visiting the platform most commonly for loan purposes of holiday or wedding or home improvement, both of which are around 15% of loan applications. 14.03% of applicants use Credit Check Sites, with usage appearing highest for those seeking auto loans (18.9% of applicants). Panel B of Table 11 reports the number of purchased loans through the two major channels for each of the loan purpose categories. Interestingly, the rate of loan purchase is higher for those arriving through the Rate Comparison channel (1,860/13,182 = 14.11% of purchased loans compared with 9.63% of applicants) relative to the Credit Check channel (1,751/13,182 = 13.28% of purchased loans compared with 14.03% of applicants).

Panel C of Table 11 reports loan purchase rates by channel for the major loan purchase categories. The final column of Panel C is the overall purchase rate for the platform by loan purpose. Generally, the loan purchase rates are much higher for those arriving through the rate comparison site channel (17.11%) to the credit check channel (11.06%) or neither source (11.11%). This is the case across all the major loan categories. For example, the unconditional purchase rate for an auto loan is 7.00% for all platform participants, but 14.99% for those arriving at the platform via a rate comparison site. In contrast, only 6.30% of applicants seeking finance for a vehicle arrived through a credit check site.

Table 11: Use of rate comparison and credit check sites, neither rate comparison or credit check sites, and total numbers by loan purposes, for Panel A: All Applications. Panel B: Purchased Loans. Panel C: Purchase rates by loan purpose for rate comparison and credit check sites, and neither rate comparison or credit check site users. The row (Proportion) refers to the overall proportion of platform applicants or borrowers who have utilised the Rate comparison, Credit Check, Neither Rate Comparison or Credit Check (Neither) and Total applicants or borrowers. T

Panel A: All Applications

	Rate Comparison Site	Credit Check Site	Neither	Total
Debt Consolidation	4,764	6,435	39,680	50,879
Auto Loan	1,548	3,606	13,921	19,075
Holiday/Wedding	1,500	1,749	9,932	13,181
Home Improvement	1,078	1,048	6,895	9,021
Other	1,978	2,999	15,740	20,716
Total	10,868	15,837	86,170	112,875
Proportion	(9.63%)	(14.03%)	(76.34%)	(100.00%)

Panel B: Purchased Loans

	Rate Comparison Site	Credit Check Site	Neither	Total
Debt Consolidation	837	874	5,293	7,004
Auto Loan	232	227	876	1,335
Holiday/Wedding	276	240	1,069	1,585
Home Improvement	266	152	1,026	1,444
Other	249	258	1,305	1,811
Total	1,860	1,751	9,571	13,182
Proportion	(14.11%)	(13.28%)	(72.61%)	(100.00%)

Panel C: Purchase Rates by Loan Purpose

	Rate Comparison Site	Credit Check Site	Neither	Total
Debt Consolidation	17.57%	13.58%	13.34%	13.77%
Auto Loan	14.99%	6.30%	6.29%	7.00%
Holiday/Wedding	18.40%	13.72%	10.76%	12.02%
Home Improvement	24.68%	14.50%	14.88%	16.01%
Other	12.57%	8.59%	8.29%	8.74%
Total	17.11%	11.06%	11.11%	11.68%

To investigate the relationship between the channel to the platform and borrower creditworthiness, we report Veda score categories for applicants from Rate Comparison Sites, Credit Check Sites, Neither, and Overall in Table 12. Applicants arriving through the rate comparison site channel exhibit credit scores in Veda score bands of “Good”, “Very Good” and “Excellent,” at rates higher than the average rate comparison site user; 4,047 (37.24% of) applicants from rate comparison sites have Veda scores in the top three categories, compared with 32.18% of applicants from Credit Check Sites and 28.80%

of all applicants. Applicants with choice over lenders, or those who are potentially higher quality borrowers, therefore may be more likely to use Rate Comparison Sites. Credit Check Site users, are more likely than the average applicant to exhibit a Veda score in the "Average" [510, 621] range (20.76% of Credit Check Site users fall into this range, compared with 14.99% of all applicants). The threshold for which the platform automatically rejects borrowers has typically fallen within this range (518 after 2013-14). Credit Check Site users may be interested in their capacity to obtain funding, rather than shopping around for the best rate. While higher quality borrowers (those in higher Veda score categories) also use credit check sites, those around the "Average" range of Veda scores do not appear to use the Rate Comparison sites, which provides some explanation for the higher acceptance rates of borrowers through the latter channel on the platform.

Table 12: Usage of Rate Comparison Site and Credit Check Site by Veda Score Range for applicants. The table reports the

Veda Score Range	Rate Comparison Site	Credit Check Site	Neither	Total
Negative	160	231	2,372	2,763
(Proportion of Category)	(5.79%)	(8.36%)	(85.85%)	(100.00%)
Zero	2,339	2,757	20,010	25,106
(Proportion of Category)	(9.32%)	(10.98%)	(79.70%)	(100.00%)
(0,509] – (Below Ave. – Average)	2,702	4,465	28,405	35,572
(Proportion of Category)	(7.60%)	(12.55%)	(79.85%)	(100.00%)
[510,621] – (Average)	1,620	3,287	12,014	16,921
(Proportion of Category)	(9.57%)	(19.43%)	(71.00%)	(100.00%)
[622,725] – (Good)	1,800	2,319	10,693	14,812
(Proportion of Category)	(12.15%)	(15.66%)	(72.19%)	(100.00%)
[726,832] – (Very Good)	1,351	1,543	7,334	10,228
(Proportion of Category)	(13.21%)	(15.09%)	(71.71%)	(100.00%)
[833,1200) – (Excellent)	896	1,235	5,342	7,473
(Proportion of Category)	(11.99%)	(16.53%)	(71.48%)	(100.00%)
Total	**10,868**	**15,837**	**86,170**	**112,875**
(Proportion)	**(9.63%)**	**(14.03%)**	**(76.34%)**	**(100.00%)**

Predicting Loan Acceptance on the platform

While platform's automated loan-decision algorithm utilises information mainly from the Veda score in determining whether an applicant will reach the 'underwriting' phase of the process, less is known about the incremental value from utilizing non-credit score information in determining which loans will be made available for purchase by the platform's lenders. In this subsection we run logistic regressions to predict loan acceptances based on ranges of Veda scores and other observable characteristics of the borrowers.

Firstly, we run model 1, a logistic regression model including indicator variables only, mainly utilising information contained in Veda scores.

$$\ln\left(\frac{p_{Accpetance,i}}{p_{NonAcceptance,i}}\right) = \beta_0 + \sum_{j=1}^{6}\beta_j VedaIndicators_j + \sum_{j=7}^{13}\beta_j StateIndicators_j + \sum_{j=14}^{18}\beta_j YearIndicators_j + \varepsilon_i \quad (1)$$

where $p_{Acceptance,i}$ is the probability that loan application i is accepted on the platform and $p_{NonAcceptance,i} = (1 - p_{Acceptance,i})$ is the complementary probability (made up of both No Quote and Declined loans). We construct indicator variables that take the value of 1 if loan applicant i has a Veda score in a particular numerical range, where the cutoff point dictating ranges is as defined by Veda. In particular, we implement *NegativeVedaIndicator*, which takes the value of 1 if the applicant's Veda score is strictly below zero, and 0 otherwise. The variable *ZeroVedaIndicator* takes the value of 1 if the applicant's score is exactly zero, and 0 otherwise. The remaining Veda score related indicator variables are similarly defined. Their corresponding ranges are: *BelowAverageVedaIndicator*, [1,519]; *GoodVedaIndicator*, [622,725]; *VeryGoodVedaIndicator*, [726,832], and *ExcellentVedaIndicator*, [833,1200]. The range for the category of Veda score omitted from the regression is *Average*, which is in the range [520,621]; coefficients from the resulting logistic regression may be considered the relative increase in log-odds for an applicant with a Veda score in the range relative to an applicant with score in the A*verage* range. If the Veda score is utilised in the platform's loan decision, we would expect positive coefficients for those in the categories "Good", "Very Good" or "Excellent" and negative coefficients for the remaining categories.

The next set of control variables we utilise relate to the geography (state of residence) of the loan applicant. For example, we construct the indicator variable *ACTIndicator*, which takes the value of 1 if the prospective borrower resides in the Australian Capital Territory, and 0 otherwise. Regional Indicator variables corresponding to the remaining Australian states and territory are constructed similarly; variable names and corresponding applicant states of residence are as follows: *QLDIndicator*, Queensland; *VICIndicator*, Victoria; *SAIndicator*, South Australia; *WAIndicator*, Western Australia; *TASIndicator*, Tasmania; *NTIndicator*, Northern Territory. The remaining state, New South Wales, is the most populous state in Australia and is considered the reference category; we do not have any expectations regarding the signs of coefficients of regional variables.

This set of variables forms the basis of model 1, the "Veda Scores Only" model, which should provide some insight into the power of simple Veda scores and regions in predicting whether loans likely to be accepted on the platform. The second model is "Veda Scores + Underwriting" which utilises other loan- and borrower-level characteristics to predict loan acceptance. Model 2 is described fully as:

$$\ln\left(\frac{p_{Accpetance,i}}{p_{NonAcceptance,i}}\right) = \beta_0 + \sum_{j=1}^{6} \beta_j VedaIndicators_j + \sum_{j=7}^{13} \beta_j StateIndicators_j + \sum_{j=14}^{18} \beta_j YearIndicators_j + \beta_{19} Age + \beta_{20} Age^2 + \beta_{21} \ln(Income) + \beta_{22} \ln\left(\frac{AmountSought}{Income}\right) + \sum_{j=23}^{26} \beta_j LoanPurposeIndicators_j + \sum_{j=27}^{29} \beta_j EmploymentStatusIndicators_j + \sum_{j=30}^{34} \beta_j OccupationIndicators_j + \beta_{35} SocioeconomicAdDisDecile + \beta_{36} RateComparisonIndicator + \beta_{37} CreditCheckIndicator + \varepsilon_i \quad (2)$$

Age is a numerical variable indicating the applicant's age in years, suspecting that older applicants may be more likely to be accepted and thus the sign of the coefficient positive. We add *Age^2* to the model, in case applicants of retirement age are less likely to obtain finance, which would result in a negative coefficient. To this we add *ln(AmountSought/Income)*, which is the natural logarithm of the amount the applicant is seeking to borrow to the applicant's reported income; loan applicants with income of zero are set as missing; *ln(Income)* is the natural logarithm of the prospective borrower's stated income.

The model is augmented with loan purpose indicator variables, which take the value of 1 if the loan applicant states the intended purpose falls into a specific category, and zero otherwise. The variable names and loan purposes are self-evident; *DebtConsolidationIndicator*, loans for Debt Consolidation; *VehicleLoanIndicator*, loans to purchase or refinance a vehicle; *Holiday/WeddingIndicator*, loans stated as for holiday or wedding purposes; and *HomeImprovementIndicator*, loans stated as for renovations or extensions to the house of the applicant. The excluded categories here are loans for vague reasons (major purchase, or other), loans classified as for "Student," or "Education Expenses", for "Family or Friends," or for "Business."

Indicator variables for the borrower's employment status are added to the model, these are: *PartTimeContractIndicator* if the applicant's employment status is "part-time" or "contract," *IrregularWorkIndicator* if the applicant is employed casually or seasonally only, and *BenefitsNoWork* indicator if the applicants occupational status is listed as "Not in Paid Employment," "Unemployed," or "Pension/Government Benefits." These three indicator variables are used to differentiate the applicant from those employed full-time; we therefore expect that the probability of acceptance will be negative for each of these three categories.

We provide further information on the loan applicants in terms of their occupation; potential borrowers' self-reported employment category falls into broad categories and indicator variables are created to represent these. The variables used here are *Professional/ManagerIndicator*, *TradeIndicator*, *Self-EmployedIndicator*, *DirectorIndicator*, and *Beneficiary/StudentIndicator*. The excluded category of employment from the dataset here is "Sales/Retail" or "Other." As this is self-reported and the category itself is relatively vague (for example an applicant may categorise themselves as "professional" although they work in sales), explanatory power here is mainly expected to arise as part of the underwriting phase of the application. Applicants who are self-employed, for instance, are likely to require additional documentation verifying their income.

The remaining set of auxiliary control variables are as follows: *SocioEconomicIndexAdDisDecile* is a variable that takes a value of between 1 and 10, higher values indicate that the applicant is from a postcode with higher average socioeconomic status, as measured by the *Australian Bureau of Statistics*. This variable should capture unobserved information from the borrower's state and, potentially, any localised aspects of disadvantage not captured by the Veda score. A positive coefficient on this variable would thus indicate a borrower from a postcode with a higher Socio-Economic Advantage and Disadvantage decile would be more likely to be accepted by the platform.

The data set also contains information on the channel that brought the customer to the platform, as indicated through cookies noting which website the applicant visited immediately prior to the platform's site. We single out two particular types of website, "rate comparison" sites and "credit score information" sites. We construct a variable *RateComparisonIndicator*, taking the value of 1 if the applicant came through the rate comparison site channel, and 0 otherwise. The variable *CreditScoreCheckIndicactor* is formed, which takes the value of 1 if the applicant arrived to the platform via the "Get Credit Score" site channel, and 0 otherwise.

Finally, we add financial year fixed effects, with the first year of platform operation, 2012-13, omitted. Any positive coefficients would indicate that applicants in subsequent years of platform operation were more likely to be accepted.

Table 13: Logistic Regression Models for Platform Loan Acceptance. The table reports the results of two logistic regression models forecasting loan acceptance on the platform (the dependent variable takes the value of 1 if a completed loan application was purchased by the platform's investors, and 0 if the loan outcome was Declined or No Quote). Model 1 reports the logistic regression in Equation (1) using Veda Score and Regional information only. Veda Scores Indicator variables take the value of 1 if: "Negative" if the Veda score is below zero, "Zero" if the Veda Score is 0, "Below Average" if the Veda score is in the range [1,519], "Good" if the Veda score is in the range [622,725], "Very Good" if in the range [726,832], and "Excellent" if in the range [833,1200], and 0 otherwise. Regional Indicator variables take the value of 1 if the loan applicant is from a particular region (mutually exclusive, with NSW as the reference region). Model 2 reports the logistic regression in Equation (2), which nests Model 1 and adds addition variable Age: the applicants Age in years), Age^2 : the squared value of the applicant's age in years, ln(Income): the natural logarithm of the applicant's income in dollars, ln(AmountSought/Income): the natural logarithm of the loan amount sought by the applicant to their income in dollars, DebtConsolidationIndicator: an indicator variable taking the value of 1 if the loan purpose is stated as Debt Consolidation, and zero otherwise, Vehicle Loan Indicator: an indicator variable taking the value of 1 if the loan purpose is stated as "Purchase or Refinance a Vehicle", and zero otherwise, Holiday/WeddingIndicator: an indicator variable taking the value of

1 if the loan purpose is stated as Holiday or Wedding, and zero otherwise, HomeImprovementIndicator: an indicator variable taking the value of 1 if the loan purpose is stated as HomeImprovement, and zero otherwise, PartTimeContract: takes the value of 1 if the applicant works part time or on a contract basis, IrregularWork: takes the value of 1 if the applicant works casually or on a seasonal basis, BenefitsNone: takes the value of 1 if the applicant is on benefits or not in paid employment, Professional/ManagerIndicator: takes the value of 1 if the applicant's occupation is stated as "Professional" or "Manager", TradeIndicator: takes the value of 1 if the applicant's stated occupation is "Trade", Self-EmployedIndicator: takes the value of 1 if the applicant's stated occupation is "Self-Employed", DirectorIndicator: takes the value of 1 if the applicant's stated occupation is "Director", Beneficiary/StudentIndicator: takes the value of 1 if the applicant's stated occupation is "Beneficiary" or "Student", SocioeconomicAdDisDecile: reports the decile of the Socioeconomic Advantage and Disadvantage for Areas in which the applicant resides (1 = lowest, 10 = highest), RateComparisonIndicator: takes the value of 1 if the applicant reached the platform through the channel of one of the Rate Comparison sites, and CreditCheckIndicator: takes the value of 1 if the applicant reached the platform through the channel of the credit score check website, and zero otherwise. Variables denoting the financial year (between July 1 and June 30) are included, indicated by FY2013-14Indicator for applications beginning between July 1 2013 and June 30 2014, and similarly for other financial years.

	1.Veda Scores Only		**2.Veda Scores + Underwriting**	
	Coefficient	(P-value)	**Coefficient**	(P-value)
Constant	-1.213	(<0.001)***	-8.528	(<0.001)***
Negative Veda Indicator	-5.413	(<0.001)***	-5.671	(<0.001)***
Zero Veda Indicator	-5.074	(<0.001)***	-5.049	(<0.001)***
BelowAverage Veda Indicator	-1.997	(<0.001)***	-2.077	(<0.001)***
Good Veda Indicator	0.902	(<0.001)***	0.949	(<0.001)***
Very Good Veda Indicator	1.213	(<0.001)***	1.348	(<0.001)***
Excellent Veda Indicator	1.194	(<0.001)***	1.590	(<0.001)***
ACT Indicator	0.516	(<0.001)***	0.230	(0.005)***
QLD Indicator	0.028	(0.303)	0.128	(<0.001)***
VIC Indicator	-0.076	(0.008)***	-0.047	(0.127)
SA Indicator	-0.295	(<0.001)***	-0.018	(0.736)
WA Indicator	0.037	0.289	-0.039	(0.306)
TAS Indicator	0.001	0.985	0.355	(<0.001)***
NT Indicator	0.247	(0.014)**	0.101	(0.347)
Age			0.069	(<0.001)***
Age^2			-0.001	(<0.001)***
ln(Income)			0.461	(<0.001)***
ln(Amount Sought/Income)			-0.339	(<0.001)***
Debt Consolidation Indicator			0.472	(<0.001)***
Vehicle Loan Indicator			0.149	(0.001)***
Holiday/Wedding Indicator			0.493	(<0.001)***
Home Improvement Indicator			0.558	(<0.001)***
PartTimeContract			-0.606	(<0.001)***
IrregularWork			-0.969	(<0.001)***
BenefitsNone			-3.277	(<0.001)***
Professional / Manager Indicator			0.112	(<0.001)***
Trade Indicator			-1.486	(<0.001)***
Self-Employed Indicator			-0.228	(<0.001)***
Director Indicator			-0.728	(<0.001)***
Beneficiary/Student Indicator			-0.953	(<0.001)***
SocioeconomicAdDisDecile			0.021	(<0.001)***

RateComparisonIndicator			0.252	(<0.001)***
CreditCheckIndicator			-0.164	(<0.001)***
FY2013-14Indicator	-0.008	(0.953)	-0.120	(0.425)
FY2014-15Indicator	-1.070	(<0.001)***	-1.324	(<0.001)***
FY2015-16Indicator	-0.760	(<0.001)***	-0.734	(<0.001)***
FY2016-17Indicator	-0.571	(<0.001)***	-0.159	(0.195)
FY2017-18Indicator	-0.402	(0.001)***	0.139	(0.298)
num. observations	112,875		108,643	
Cox-Snell R^2	0.165		0.237	

Table 13 reports the results of the logistic regression models of loan acceptance against Veda score and other control variables. Model 1 is the nested model, containing only information on Veda scores, regions, and year fixed effects. The coefficients for the variables *NegativeVedaIndicator and ZeroVedaIndicator* are negative and highly significant (-5.413 and -5.074, respectively) indicating that, relative to an applicant with an average Veda score, applicants with negative Veda scores are 1/exp(-5.413)=224 times less likely to be accepted on the platform, ceteris paribus.

Examining Model 1 we broadly see the expected sign and magnitude of the Veda score range indicator variables. Veda scores above average all increase the prospect of loan acceptance, while those below average decrease the probability of loan acceptance. A small quirk is presented by the Veda scores in the Excellent range having a marginally lower coefficient than odds in the Very Good range, although this effect is only marginal (1.194 vs. 1.213), leading to predicted acceptance rates of 76 and 77%, respectively.

Geographical (state-level) effects indicate that, relative to applicants from New South Wales, those from the ACT and Northern Territory are more likely to have loans accepted, while those applicants from Victoria and South Australia have slightly lower acceptance likelihoods. The relatively large coefficient for applicants from the ACT indicates a 16% increase in acceptance probability in this basic model.

Financial year fixed effects are either insignificant (2013-14) or significantly negative in Model 1, indicating that in years subsequent to the platform's foundational year (2012-13) the probability of acceptance has declined. This is likely a function of the sharp increase in the number of people utilising the platform, rather than more prudent loan approvals.

Model 2 in Table 13 augments Model 1 with additional 'underwriting' variables that a typical loan assessor might consider when deciding to accept or reject an applicant on the platform. The constant β_0 is substantially more negative in this model, as added variables have included numerical factors with non-zero mean, such as *Age* and *ln(Income)*. The coefficients of variables that were previously incorporated into Model 1, particularly those relating to Veda score, are materially similar in Model 2. Noticeably, *ExcellentVedaScore* exhibits a coefficient larger in magnitude than *VeryGoodVedaScore*

(1.590 vs. 1.348), which was not the case in Model 1. Applicants from the ACT remain significantly more likely to be accepted by the platform than those from NSW, although the coefficient has decreased substantially, suggesting that incorporating other variables has explained much of the state-level variation in loan acceptance. In a similar fashion, applicants from Queensland and Tasmania are now more likely to be accepted, conditional upon the other factors in the model.

Examining the other variables in Model 2, *Age* is positive and significant, while Age^2 is negatively signed; probability of loan acceptance is a quadratic function of the age of the applicant. Older applicants are less likely to benefit from access to the credit provided, relative to working-age individuals. The natural logarithm of an individual's income, *ln(Income)*, is positively related to loan acceptance, as those applicants are expected to be able to service the loan better. The average value of income in the data set is $43,470, and only applicants reaching the underwriting phase of the process have their incomes verified; thus income may be somewhat less powerful a tool in predicting loan acceptance in this data set. Examining the related variable, *ln(Amount Sought / Income)*, indicating the applicant's capacity to service a potential loan, the negative coefficient confirms it to be the case that applicants with a lower capacity to service the loan are less likely to be accepted. With a mean value of -1.23, this variable helps more to predict applicants that will be denied funding (i.e. those with relatively large values of this variable) than those who will obtain funding from the platform.

The set of loan purpose indicator variables are all positive and significant, including those for debt consolidation and home improvement. Holding debt in other forms does not preclude applicants from obtaining funds through SocietyOne, it may in fact be beneficial to applicants with extant debts to exhibit informative Veda scores. Loan categories that are specifically for consumption purposes (Holiday/Wedding) are more likely to be approved than loans from the omitted reference categories (here, student or educational loans, loans for other people or business reasons).

Employment attributes are, as expected, a key determinant in loan acceptance as they form a crucial aspect of the underwriting process. Relative to full-time employees, part-time or contracted employees, as seen from the negative coefficient of *PartTimeContract*, are less likely to have their loans purchased on the platform, as are those with irregular or seasonal work (*IrregularWork*). Applicants on benefits or not in paid employment (represented by the variable *BenefitsNone*) are extremely unlikely to be accepted by the platform. Occupation type, from the broad categories provided in the dataset, has some relevance in predicting loan acceptance. Applicants who have indicated that they are "Professionals" or managers have a higher probability of loan acceptance than those in the reference category, "Other" or "Sales/Retail," although this appears relatively minor in magnitude. The main source of predictive power comes from the negative coefficients attached to the occupations which are either self-employed (*Self-Employed* or *Trade*) or less likely to have reliable income (*Director*). Each of these categories is less likely to obtain funding than the broad "Other" or

"Sales/Retail" category. As expected, those applicants with stated occupation of "Benefits" or "None" are highly unlikely to see their loan applications fulfilled.

The remaining variables are somewhat more novel with regards to loan underwriting (although unlikely to be used in practice). The coefficient of the variable *SocioeconomicAdDisDecile* is positive and significant, indicating that there are some unobserved, localised factors in the model for predicting loan acceptance. That is, potential loan applicants from low socio-economic areas are less likely to be accepted on the platform, even after accounting for Veda scores, income, age, and employment status. Interpreting the coefficient is most easily seen from an odds ratio perspective, the coefficient of 0.021 indicates that the odds of loan acceptance increase by $\exp(0.021 * d)$ for decile d increase in the socioeconomic index. The odds difference for someone in decile 10 (the highest socioeconomic areas) compared to decile 1 is thus $\exp(0.021 \times 9) = 1.21$. The fact that this variable is significant suggests that potentially not all information about potential borrowers is captured in Veda scores; borrowers living in low socioeconomic areas are less likely to obtain credit, ceteris paribus, than borrowers in high socioeconomic areas. Based purely from the acceptance rates by socioeconomic status (i.e. ignoring the effects of other variables) the acceptance rate for borrowers in decile 10 of the SEIFA index were accepted on 16.9% of occasions, versus 6.8% for borrowers from decile 1.

Borrowers that were directed to the platform through the "rate comparison" channel were more likely to have their loans accepted than those that were not, with a highly significant coefficient of 0.252. This increase in acceptance likelihood may confirm the anecdotal evidence that patrons of rate comparison sites are of a sophisticated nature and more willing to shop around for the low-cost loans. By way of contrast, loan applicants that arrived through the channel of "credit check" sites were less likely to see their loan accepted. This may be due to the fact that people with blemishes on their credit record are more likely to check their credit score, or simply aim to find out whether their Veda score would preclude them from obtaining funding. These findings may provide useful guidance to underwriters for personal loans elsewhere.

The final concern of the logistic regressions are the indicator variables for the financial year in which the application was commenced. The incremental information from the underwriting variables does not substantially alter the contention that the platform's growth is due to declining loan standards. Indicators for 2014/15 and 2015/16 are negative and significant, while other year indicators are not significant. We conclude that conditional on other factors, the likelihood of loan acceptance has not increased although the platform growth has been substantial. Declining loan standards do not, in other words, appear responsible for the growth of the platform.

The nested model (Veda scores only) is clearly outperformed by the full model in terms of predicting loan outcomes; the Cox-Snell R^2 increases from 0.165 to 0.237; perhaps this is not surprising given the fact that variables including income were added to the model, but it is clear that the platform is not making lending decisions based purely on the basis of Veda scores. Examining the ROC curve in Figure 5 (below), it is noticeable that the incremental improvement in predictability is throughout the range of probabilities for the full model. The additional 'underwriting' variables help forecast both those who obtained loans and those that did not. Arguably, this difference could be considered the difference between the quality of credit information contained in the Veda score, and potential improvements that could be realised through comprehensive credit reporting.

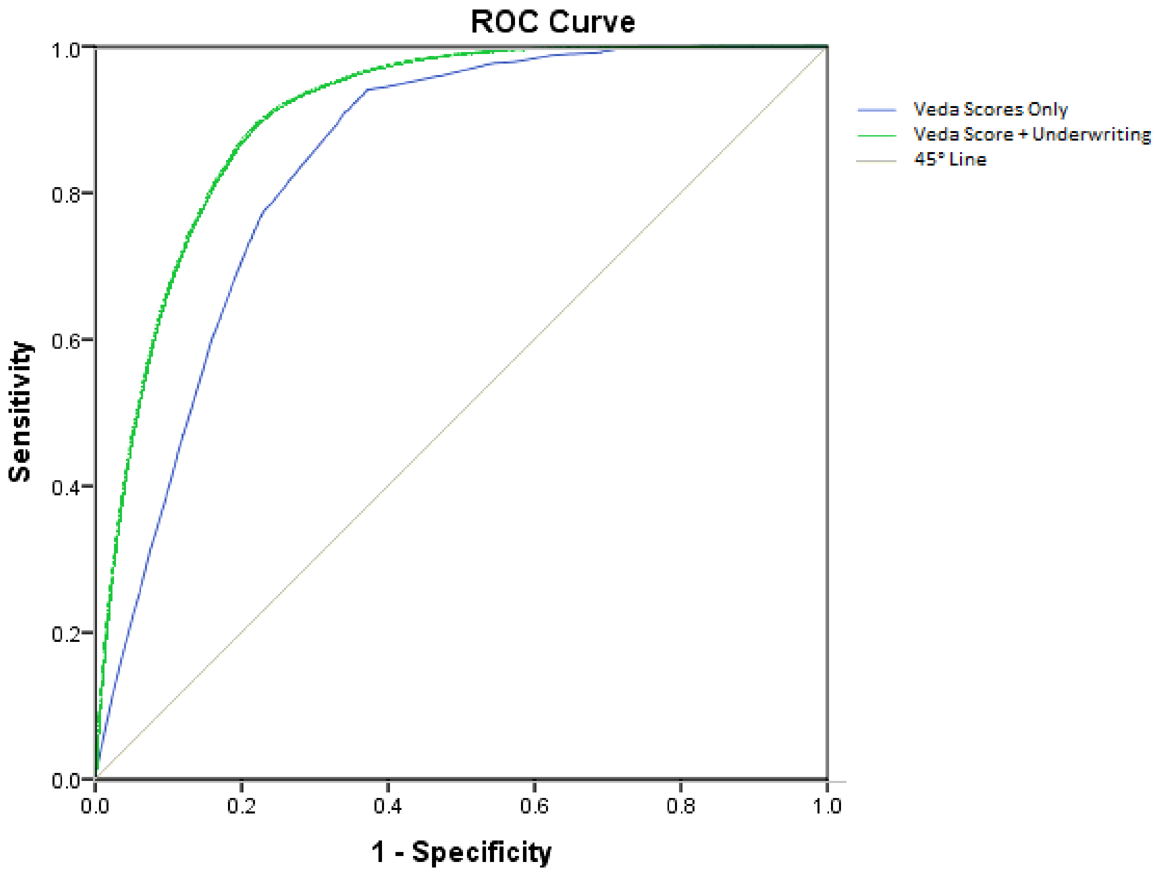

Figure 5: ROC curves for Model 1 and Model 2 from Table 13. The Blue line represents Model 1, while the Green line represents Model 2 (Veda scores + underwriting).

Conclusions

This paper has examined the structure and determinants of loan funding on largest consumer lending marketplace platform in Australia, Society One. Using a unique dataset provided by Society One, we were able to observe all fully and partially completed loan applications, and compared these against loans accepted by the platform over a five-year period. The platform uses a two-stage credit risk screening process. Applications are initially filtered through an automated decision tree based on a third-party credit score (Veda score). Subsequently, performs manual underwriting via credit checks and assessments under the Responsible Lending regulatory requirements in Australia (ASIC 2014) before accepted loan applications are offered to wholesale and sophisticated investors. Debt consolidation is one of the core functions of the platform, with 45.07% of applications, and 53.12% of purchased loans seeking funding for this purpose.

Loan application acceptance conformed to credit variables, such as the applicant's Veda score, as well as employment status, income, and loan to value ratio. Successful applicants had higher Veda Scores, with 76.55% of loans are purchased from borrowers with Veda scores classified as "Good", "Very Good," or "Excellent," with the lower bound for good set at a score of 622.

Additional variables were also involved in manual underwriting decisions. We present logistic regression models indicating that variables that may be utilised in the underwriting process. Variables relating to employment status, age, income, and loan to income ratio all exhibit significant coefficients in the expected direction when added as auxiliary variables to a model containing Veda scores. Incorporating these variables that we might expect to be used by underwriters shows that loans are more likely approved only after verification. We found that the growth in loan volume through the platform does not appear to be driven by a decline in lending standards. In addition to data provided by the platform, we also incorporated data and analysis on applicant's geographic locations, in terms of socioeconomic advantage and disadvantage, as measured by the Australian Bureau of Statistics' SEIFA index (ABS 2013) and loan funding outcomes. Applicants SEIFA location, is strongly related to loan acceptance by Society One. Applicants from the lowest decile of socioeconomic areas in Australia exhibit an acceptance rate of 6.84%, compared to the acceptance rate of 16.87% for applicants in the highest socioeconomic decile. We demonstrate that applicants from higher socioeconomic deciles have higher Veda scores, are more likely to be employed full-time, and more likely to apply for personal loans for debt consolidation purposes, relative to applicants from lower socioeconomic deciles.

There also appears to be some forecasting power for loan acceptance based on the link to the platform's website. We identify applicants who visited the platform through two separate channels, rate comparison sites, which show borrowers the rates available on personal loans from a large selection of providers, and credit check sites, which allow borrowers to find out their Veda score and provides information regarding their creditworthiness with lenders. Applicants arriving at the platform through a rate comparison site are more likely than the average applicant to be funded, while those using credit check sites are less likely to be funded. In part, this reflects the higher average Veda score of those using rate comparison sites compared with credit check sites. It provides some evidence that people with lower search costs, who use the comparison sites, or those who are more financially literate in this case, are more likely to be funded. Alternatively, we find those who are uncertain about their capacity to obtain funds appear to be the most likely applicants to use credit check sites; the modal Veda range of applicants from comparison sites is [510, 621], or “Average” according to Veda.

While our paper looks at borrower characteristics as predictors of loan application success, we are also interested how new online consumer loan marketplaces fit into existing credit markets. In this respect our paper is related to the banking literature and to research which examines the relationship between new online credit markets and banking. Our findings suggest that loan funding on the platform in mainly to prime borrowers and that debt consolidation was a major reason for borrowers seeking loan funding. We also found that growth in loan volume through the platform does not appear to be driven by a decline in lending standards. Evaluating loan performance will add further insight into where such loan marketplaces fit in relation to consumer credit markets.

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Appendix A

Figure 6: Flow Chart of Society One Loan Decision Model