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What Drives Defaults in Australian FinTech Credit Market?

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1. Introduction

The online lending markets have shown the ability to match buyers and sellers more efficiently than the traditional markets and convert businesses to a new era. They provide market participants easy and fast service, an instant transactions, a level of trust with other participant, and relatively low costs. In this study, we will cover Peer-to-peer (P2P) lending, which is an online lending markets in FinTech. P2P lending enables individual borrowers to access financing from other individual lenders via an online platform for a fee.

The analysis of the determinant of default risk is important as it provides signals for the market participants when the financial sector becomes susceptible to shocks. This can help the policy makers to take steps to avoid any potential crisis. Understanding the default risk is especially important in non-bank lending sector, so called "shadow banking". Lending outside the banking sector proved to be much more vulnerable which was evident during the COVID-19 induced economic turmoil of 2020. Sudden demands for cash necessitated extraordinary interventions by the Federal Reserve to prevent a broader market meltdown. (Dudley 2021)

As first research question, this study aims at analyzing factors explaining the default risk in P2P lending. This paper empirically analyzes the relationship of the borrowers' personal characteristics such as annual income, indebtedness and credit history and the interest rate and the default risk. It also adopts a set of hypotheses on the relationship between the macroeconomic factors and the default risk in peer-to-peer lending. These factors are inflation and stock market index. We develop the hypotheses related to these two macroeconomic factors in section 2.2 of this paper.

2. Literature review and hypotheses development

2.1 Background literature

Credit and default risk are used simultaneously which is defined as the risk arising from inability of the borrower partially or totally repay the loan to the lender. Two streams in the existing literature focused on the main factors that influence the default risk in the traditional financial markets. One stream considers internal variables as a determinant of credit risk which is called unsystematic credit risk such as personal characteristics and financial solvency for individuals and management, financial position, corporate governance for firms. The other stream considers systematic credit risk which results by external factors such as the macroeconomic factors, changes in economic policies, and political changes.

Few studies examined macroeconomic factors that may influence P2P lending. However, there is a great deal of academic research examining macroeconomic factors that affect the credit risk in banking sector. For example, Castro (2013) studied the relationship between the macroeconomic variables and credit risk in banking system in Greece, Ireland, Portugal, Spain and Italy. By using data over the period of 1997–2011, the researcher found the credit risk is negative affected by GDP growth, share price indices and housing price index, and positively affected by unemployment, interest rate, exchange rate and credit growth rate.

Salas and Saurina (2002) compared the determinants of the default risk between commercial and savings banks in Spain over the period 1985 – 1997. They studied the macroeconomic and microeconomic variables that explain the credit risk. They found that GDP growth rate and the families' indebtedness level (Firms indebtedness level) have a negative (positive) effect on the default risk for both commercial and savings banks. Similarly, Zribi and Boujelbegrave (2011) studied macroeconomic and microeconomic factors of default risk in the banking sector in Tunisia. They found that the ownership structure and profitability (prudential regulation of capital, GDP growth, inflation, exchange rate and interest rate) influence the bank credit risk positively (negatively). Kjosevski, Petkovski, and Naumovska (2019) examined the influence of macroeconomic and bank-specific determinants on the default risk to firms and individuals by using a sample of banks in the Republic of Macedonia. They found that the unemployment and banks solvency (banks' profitability, the growth of loans and GDP growth) have a positive (negative) impact on the non-performing loans (NPLs).

Using a panel data for 18 European countries during the period 2000–2011, Messai and Gallali (2019) studied the macroeconomic determinants of default risk in the banking system. By using a P-VAR approach, they found a positive (negative) relationship between the credit risk and inflation rate and unemployment rate (share price index and GDP growth rate). Chaibi and Ftiti (2015) also investigated the effect of macroeconomic and bank-specific factors on loan quality and compared the results between two different banking systems, namely the market-based system in France, and bank-based system in Germany. The results indicate that the GDP growth (unemployment) influence the default risk negatively (positively) in both countries. There were differences between two banking systems in the influence of exchange rate and inflation on the credit risk. On the contrary of Germany, they found the effect of exchange rate is positive in France. They also found the inflation is negatively related with the default risk in Germany, while the result was statistically insignificant in France.

In P2P lending market, Wang and Ni (2020) examined the monthly trend of the default rate at the aggregate level for the P2P data over the period 2007-2016. By using the long-short term memory (LSTM) approach, they find that macroeconomic factors such as unemployment rate and GDP growth need to be considered when analysing the factors that affect the default rate in the P2P market. As mentioned earlier, the systematic credit risk factors in P2P lending are under the attention of a few studies. For instance, Foo, Lim, and Wong (2017) found that the unemployment rate, investor uncertainty, and the fundamental value of the market are shown to be closely correlated to P2P loan default. Nigmonov et al. (2022) analysed P2P lending defaults in the US and indicated that inflation and interest rates are positively associated with loan defaults.

The second stream of the literature investigated unsystematic credit risk, microeconomic factors, for individuals on the default risk within P2P lending markets. Chemin and Laat (2013) investigates the lending behaviour of Western investors to enterprises in poor countries on P2P lending platforms. Utilising MYC4 platform data, they found that Western lenders offer loans to pro-poor, socially responsible, and pro-female African projects at lower interest rates. More importantly, they found evidence of a positive relationship between interest rates and default risk. In their efforts to examine the success rate between genders in securing funds using P2P lending platforms, Barasinska and Schäfer (2014) found that in Germany, women have higher chances of securing funds on P2P lending platforms. Furthermore, they documented a positive effect of interest rates and borrower's financial burdens on default risk. They also found that loan amount is negatively related to default risk.

Gu and Yao (2015) examined data collected from WDW Shanghai platform to determine factors of default risk on P2P lending platforms. They found that household register, marital status, and past defaults affects default rate. Moreover, they found a positive relationship between Debt to Income (DTI) ratio and default rate. In contrast, they found a negative relationship between credit grade, family awareness of the loan, and the truth of borrowing purpose and default risk. Using US Lending Club data, Serrano-Cinca, Gutiérrez-

Nieto, and López-Palacios (2015) investigated the determinants of default risk in P2P loans. They documented an evident relationship between the purpose of the loan and default risk. Specifically, loans that are intended to pay for weddings are considered as a less risk loan, while seeking funds for a small business is the riskiest. Moreover, they found that the current housing situation, credit history, and indebtedness are associated with default risk. Additionally, they found that number of loan requests, loan's amount and DTI are negatively associated with default risk. Furthermore, they found that credit rating grades assigned by Lending Club are positively associated with the default risk. Hence, an A-grade loans is the safest and G-grade loans are the riskiest.

Emekter, Tu, Jirasakuldech, and Lu (2015) documented a positive (negative) relationship between credit ratings (debt-to-income ratio) and default risk. In contrast, Malekipirbazari and Aksakalli (2015) found that credit ratings do not provide a clear indication of borrower's default risk. Guo, Zhou, Luo, Liu, and Xiong (2016) used data from Lending Club and Prosper, they found that loan's amount, numbers of loan requested, and home ownership are positively related to default risk. While DTI ratio, and credit ratings and default risk are negatively related.

Using Chinese borrowers' demographic characteristics and corresponding loan information, X. Lin, Li, and Zheng (2017) examined the factors that affect the default risk on P2P loans. They found that gender, age, marital status, educational level, working years, company size, monthly payment, loan amount, debt to income ratio and delinquency history play a significant role in loan defaults. Specifically, borrower's gender (female), age (young), working experience, marital status (married), education (high), company size (large), monthly payment (low), loan amount (low), DTI ratio (low), and no previous defaults are associated with low risk of default.

Likewise, Gaigalienė and Česnys (2018) investigated the determinants of default risk in the Lithuanian P2P market. They found that borrower's education (higher than high school), working experience, gender (female), and marital status (married), credit ratings, and DTI ratio has a negative effect on default risk. In contrast, they documented a positive effect of loan period, interest rate, and age on default risk. Furthermore, they suggested that a loan purposed for a car purchase has decreases the default risk, while business loans have increases default risk.

In another study focusing on China, Hu, Liu, He, and Ma (2019) collected data from Renrendai P2P lending platform to investigate investors capabilities to identify default risk. They found an irregular relationship between interest rates and default risk; specifically, loans with similar interest rates can have different default risks. Additionally, contradicting other studies, they found a positive relationship between borrower's income (high) and default risk. They found that lenders usually ignore the effects borrower's personal characteristics (income, age, and education) on default risk, but focuses on borrower's creditworthiness, loan's amount, and loan's term, which it turns out to be the key factors in assessing borrowers' default risks.

Lee (2020) developed a model to test the default risk in P2P loans. The researcher found that small and short-term loans with low interest rates have a low default risk. Also, there was evident that borrower's financial conditions are negatively related to default risk. Moreover, the Author found that loan's purpose affects default risk; specifically, loans used to fund small business have higher default risk. Furthermore, Croux, Jagtiani, Korivi, and Vulanovic (2020) found that borrowers with high default risk have long maturity loans (5-year loans), lower credit scores, are renting, work as labourers, and using loans to fund medical expenses or small business. While, borrowers with low default risk seek loans to finance weddings, house related, and car purchases, furthermore, they are a white-collar worker. Additionally, Santoso, Trinugroho, and Risfandy (2020) examined the default risk of P2P loans in Indonesia. Using data collected from Indonesia Financial Services Authority, they find a positive relationship between default risk and interest rates, amount of the loan, loan term (long-term loans), income (high), age, and gender (female). Whoever, marital status (married), home ownership, education (higher degrees), is negatively related with default risk.

Prior studies also examine the influence of friendships and social networks on P2P lending default risk. For example, M. Lin, Prabhala, and Viswanathan (2013) examined the effects of online friendships of borrowers on default risk. Using data from Prosper.com they found a negative relationship between borrower's friendship network and default risk. Freedman and Jin (2017) investigated the relationship between social ties and probability of default in P2P platforms, and they found a positive relationship between social ties and default risk.

In conclusion, it is evident that macro and microeconomics and personal characteristics have an influence on P2P loan default risk. Previous literature provides evidence that interest rate, inflation, unemployment, credit options, loan's purpose, amount and maturity, and borrower's credit score, income, age, marital status, gender, home ownership, DTI ratio and education influences default risk in different context. Hence, to the best of our knowledge, there is no studies that examine the effects of macroeconomics and personal characteristics on default risk in the Australian P2P lending market. Therefore, the current study will investigate the influence of inflation and stock market development on P2P loan default risk in Australia.

2.2 Hypotheses development

Hypothesis 1: Inflation has a positive impact on P2P lending markets.

The growing theoretical literature describes mechanisms whereby even predictable increases in the rate of inflation interfere with the ability of the financial sector to effectively allocate resources. More specifically, recent theories emphasise the importance of informational asymmetries in credit markets and demonstrate how increases in the rate of inflation adversely affect credit market frictions with negative repercussions for financial sector performance and, therefore, for long-run real activity (Huybens & Smith, 1998). The common feature of these theories is that informational friction is viewed as having an endogenous level of severity. Given this feature, an increase in the rate of inflation drives down the real rate of return not only on money, but also on assets in general. The implied reduction in real returns exacerbates credit market frictions. As these market frictions lead to the rationing of credit, as inflation rises, credit rationing becomes more severe. As a result, the financial sector makes fewer loans, resource allocation is less efficient and intermediary activity diminishes, with adverse implications for capital investment. The reduction in capital formation negatively influences both long-run economic performance and equity market activity, where claims to capital ownership are traded (Boyd, Levine, & Smith, 2001). Thus, asymmetric information creates a circle of causations from the real economy to the financial sector and around to the real economy again.

Hypothesis 2: Stock market development has a negative impact on P2P lending markets.

From the hypothetical viewpoint P2P lending and crowdfunding markets are poised for development when the financial markets do not function well. In this respect, some of the existing studies indicated that at places where financial intermediaries do not function or where financial markets are underdeveloped, alternative investment opportunities blossom (Buchak, Matvos, Piskorski, & Seru, 2018; Thakor, 2020). However, the author did not find a single study that particularly considered stock market development. Therefore, the expected result of the test of this hypothesis is ambiguous.

3. Methodology

In this study, we use multiple regression model with binary outcomes as a main tool of analysis. We estimate the regression model using the logit estimation method. The calculation for this model is done using STATA software. The regression model can be written as:

$$\gamma_{\mathrm{i}} = \alpha + \beta_{\mathrm{M}} X^{\mathrm{M}} + \beta_{\mathrm{K}} X^{\mathrm{K}} + \beta_{\mathrm{B}} \mathrm{X}^{\mathrm{B}} + \beta_{\mathrm{D}} \mathrm{D} + \varepsilon_i \; [1]$$

$\gamma_{\mathrm{i,t}}$ – variable indicating the loan status. 1 if the loans status is default or late and 0 otherwise.

$\beta_{\mathrm{M}} X^{\mathrm{M}}$ - vector of macroeconomic variables (inflation and stock market index).

$\beta_{\mathrm{K}} \mathrm{x}^{\mathrm{K}}$ – vector of loan specific variables.

$\beta_{\mathrm{B}} \mathrm{X}^{\mathrm{B}}$ - vector of borrower specific variables.

β_{D}D- State specific categorical variable. One of the main purposes of the study is to reveal the specifics of P2P lending loans issued in specific region. The value of the coefficient and its significance will show the degree of difference between individual Australian states.

4. Results and discussion

4.1 Description of data

This chapter uses the aggregated loan-book database from RateSetter, Australia. The scope of this study covers the loans issued in Australia by RateSetter. RateSetter makes its loan book publicly available. The database consists of loans issued between 2014 and June 2020. We combined loan book database with inflation (CPI) and stock market index (INDEX) data. Table 1 provides the descriptive statistics of the database. This study reports a correlation matrix for the dependent, explanatory and control variables in Table 2. The table indicates low levels of Spearman's rank correlation coefficients for all of the variable pairs with few exceptions. The low levels of correlation allow us to avoid the problem of multicollinearity in regression analysis.

Table 1. Descriptive statistics

	MEAN	SD	MIN	MAX
DEFAULT	0.0504	0.2188	0	1
CPI	114.2442	2.3114	106.8	117.4
INDEX	6058.1330	489.9734	4546	7162.5
LOANTERM	42.4313	21.5428	6	84
ANNUALRATE	0.0669	0.0228	0.0205	0.165
FINANCEAMOUNT	13973.8300	12617.0900	110	456609
PRINCIPALOUTSTANDING	5755.5020	11106.9600	0	456609.2
FINANCEPURPOSE	6.7768	3.9689	1	17
EARLYPAYMENT	1.4633	0.4986	1	2
BORROWERINCOME	2.2991	0.9617	1	4
HOUSINGSTATUS	2.2528	1.4033	1	4

Table 2. Correlation matrix

	DEFAULT	CPI	INDEX	LOANTERM	ANNUAL RATE	FINANCE AMOUNT	PRINCIPAL OUTSTANDING
DEFAULT	1						
CPI	-0.0241***	1					
INDEX	-0.00426	0.762***	1				
LOANTERM	-0.00646	0.311***	0.176***	1			
ANNUALRATE	0.0587***	-0.106***	-0.136***	0.668***	1		
FINANCEAMOUNT	0.0116**	0.0290***	0.0297***	0.199***	0.289***	1	
PRINCIPALOUTSTANDING	-0.00770	0.359***	0.255***	0.294***	0.156***	0.709***	1
FINANCEPURPOSE	-0.0516***	0.116***	0.0416***	0.0789***	-0.265***	-0.275***	-0.0665***
EARLYPAYMENTSMADE	-0.123***	-0.335***	-0.216***	-0.346***	-0.139***	-0.0756***	-0.388***
BORROWERSTATE	0.00471	-0.0215***	-0.0127**	-0.0227***	-0.00526	-0.0308***	-0.0272***
EMPLOYMENTSTATUS	0.0316***	-0.0373***	-0.0220***	-0.0629***	-0.0673***	0.00132	0.00742
BORROWERINCOME	-0.0278***	0.147***	0.0757***	0.173***	-0.0608***	-0.0565***	0.0528***
HOUSINGSTATUS	0.103***	-0.0653***	-0.0216***	-0.0984***	0.0839***	0.0539***	-0.00119

	FINANCE PURPOSE	EARLY PAYMENTS	FINANCE PURPOSE	BORROWERS TATE	EMPLOYMENT STATUS	BORROWER INCOME
FINANCEPURPOSE	1	-0.0413***	1			
EARLYPAYMENTSMADE	-0.0413***	1	-0.0413***			
BORROWERSTATE	0.0297***	0.0139**	0.0297***	1		
EMPLOYMENTSTATUS	0.107***	0.0239***	0.107***	0.00609	1	
BORROWERINCOME	0.246***	-0.133***	0.246***	-0.00819	0.0853***	1
HOUSINGSTATUS	-0.381***	-0.0222***	-0.381***	-0.0691***	-0.0805***	-0.126***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Results of regression analysis

Estimation results for regression involving defaults as the binary dependent variable are reported in Tables 3 and 4. Results are based on logistic regression estimation with constant. Sampling size consists of 47,231 valid observations (N=47,231) across all states of Australia. We report the models related to the impact of inflation on default in Table 3, while the models related to stock market index are reported in Table 4. We run the regression models with three different sets of control variables. Model (1) includes loan specific control variables (loan term, loan type, etc.); Model (2) includes loan and borrower specific variables (borrower employment type, income, etc.); Model (3) includes state individual effects together with loan and borrower specific variables.

The fit of the models in Table 3 based on pseudo-R-squared values varies from 0.0452 to 0.0633. Overall fit of the model increased as we added more control variables. Models (1-3) in Table 3 depict the probability of default as a function of CPI and various control variables. The coefficients for CPI index significantly positive across all 3 models varying around 0.0003. This finding indicates that inflation significantly and positively affects delinquency rates represented by the probability of default (DEFAULT). It falls in line with the results documented in earlier studies of Skarica (2014) and Klein (2013). Most of the existing studies concerned the NPLs for loans issued by commercial banks, while our study is the first one to document such relationship in Australian P2P lending market.

Table 3. The impact of inflation to the probability of default

Note: Table 3 presents the results of logit regression analysis for the likelihood of loan default (DEFAULT) and CPI. Number of loans analysed: 49,928. On schedule or repaid: 47,417 (94.97%). Default, late or in hardship: 2,511 (5.03%). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)
	DV=DEFAULT	**DV=DEFAULT**	**DV=DEFAULT**
CPI	0.0248**	0.0189*	0.0180*
	(0.0107)	(0.0108)	(0.0108)
LOANTERM	0.0105***	0.0097***	0.0097***
	(0.0025)	(0.0025)	(0.0025)
ANNUALRATE	0.6246***	0.5511***	0.5420***
	(0.1134)	(0.1131)	(0.1131)
FINANCEAMOUNT	-0.1824***	-0.1293***	-0.1290***
	(0.0337)	(0.0345)	(0.0346)
Loan reason			
CAR/VEHICLE	-0.7792***	-0.6105***	-0.6051***
	(0.1507)	(0.1550)	(0.1552)
DEBT CONSOLIDATION	-0.7595***	-0.5510***	-0.5474***
	(0.1465)	(0.1513)	(0.1514)
HOME IMPROVEMENT	-1.2148***	-0.6436***	-0.6405***
	(0.1592)	(0.1649)	(0.1650)
INVESTMENT	-0.8255***	-0.6536***	-0.6575***
	(0.2321)	(0.2355)	(0.2356)
MAJOR EVENT	-0.5816***	-0.4198***	-0.4156**
	(0.1571)	(0.1614)	(0.1615)
MAJOR PURCHASE	-0.5685***	-0.4254**	-0.4206**
	(0.1872)	(0.1908)	(0.1909)
OTHER CONSUMER LOANS	-0.6390***	-0.4510***	-0.4504***
	(0.1604)	(0.1648)	(0.1649)
PROFESSIONAL SERVICES	-0.2212	0.2131	0.2168
	(0.1512)	(0.1553)	(0.1555)
RENEWABLE ENERGY	-3.5915***	-2.9624***	-2.9647***
	(0.2529)	(0.2619)	(0.2620)
SOLAR BATTERY	-3.3687***	-2.7779***	-2.8576***
	(0.5281)	(0.5313)	(0.5364)
SOLAR ENERGY BATTERY	-3.8480***	-3.1106***	-3.1327***
	(1.0151)	(1.0163)	(1.0164)
SOLAR ENERGY EQUIPMENT	-2.5263***	-1.8520***	-1.9119***
	(0.5991)	(0.6012)	(0.6016)
SOLAR ENERGY PANELS	-2.3851***	-1.6868***	-1.6842***
	(0.2143)	(0.2197)	(0.2196)
Employment status			
EMPLOYED FULL TIME		-0.1682	-0.1732
		(0.1685)	(0.1687)
EMPLOYED PART TIME		0.0241	0.0165
		(0.1797)	(0.1799)
HOUSEPERSON		0.4353	0.4518
		(0.6267)	(0.6270)
RETIERD/OTHER		-0.0615	-0.0549
		(0.2576)	(0.2579)
SELF-EMPLOYED		0.5208***	0.5212***
		(0.1817)	(0.1819)
BORROWER INCOME		0.0575**	0.0568**
		(0.0266)	(0.0266)
Home ownership status			
OWN A HOME (No mortgage)		-0.2623**	-0.2500**
		(0.1211)	(0.1213)

TENANT (Mortgage)		0.1585 (0.1000)	0.1619 (0.1001)
TENANT (No mortgage)		0.7708*** (0.0512)	0.7862*** (0.0515)
Residence			
NSW			0.3671* (0.1888)
NT			0.6140** (0.2509)
QLD			0.3453* (0.1893)
SA			0.4794** (0.2052)
TAS			0.5585** (0.2561)
VIC			0.3199* (0.1898)
WA			0.5548*** (0.1925)
LR CHI2	900.5849	1239.3668	1260.6365
PROB > CHI2	0.0000	0.0000	0.0000
PSEUDO-R-SQUARED	0.0452	0.0623	0.0633
N	49928.0000	49928.0000	49928.0000

Table 4 reports the results of models with stock market index (INDEX) as independent variable of interest. The fit of the models in Table 4 based on pseudo-R-squared values varies from 0.0460 to 0.0640. Overall fit of the model increased as we added more control variables. The coefficients for INDEX are significantly positive across all 3 models varying from 1.2426 to 1.4085. This finding indicates that stock market index significantly and positively affects delinquency rates represented by the probability of default (DEFAULT). Empirical evidence suggests that stock market returns are negatively associated with default risk (Mateev, 2019; Norden & Weber, 2009). Our finding contradicts these earlier studies in traditional financial markets and highlights the specifics of P2P lending market.

Table 3 and 4 also deliver several results regarding control variables that might have important implications. We find that the probability of default increase with an increase in loan maturity (LOANTERM) and loan interest rate (ANNUALRATE). On the other hand, loans with higher loan amount (LOANAMOUNT) tend to have lower default probability. We also observe significant difference in default probabilities based on loan purpose. We observe that the loans obtained for Solar Energy or renewable batteries are least risky in terms of the likelihood of default[1]. Borrowers who are employed full-time are less likely to default compared to part-time employees, while homeowners are less likely to default compared to borrowers who rent their dwellings. We find that borrowers who reside in Northern Territory are most likely to default if compared with other states and territories of Australia[2].

[1] Our model takes the business loans as the base group in 'loan purpose' categorical variable.
[2] Our model takes the Australian Capital Territory (ACT) as the base group in 'Residence' categorical variable.

Table 4. The impact of stock market index to the probability of default

Note: Table 4 presents the results of logit regression analysis for the likelihood of loan default (DEFAULT) and INDEX. Number of loans analysed: 49,928. On schedule or repaid: 47,417 (94.97%). Default, late or in hardship: 2,511 (5.03%). All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

	(1)	(2)	(3)
	DV=DEFAULT	**DV=DEFAULT**	**DV=DEFAULT**
INDEX	1.4085***	1.2619***	1.2426***
	(0.3101)	(0.3114)	(0.3115)
LOANTERM	0.0085***	0.0075***	0.0075***
	(0.0024)	(0.0025)	(0.0025)
ANNUALRATE	0.7317***	0.6645***	0.6570***
	(0.1119)	(0.1115)	(0.1115)
FINANCEAMOUNT	-0.1856***	-0.1326***	-0.1324***
	(0.0338)	(0.0346)	(0.0346)
Loan reason			
CAR/VEHICLE	-0.7923***	-0.6240***	-0.6191***
	(0.1505)	(0.1548)	(0.1549)
DEBT CONSOLIDATION	-0.7776***	-0.5709***	-0.5679***
	(0.1462)	(0.1510)	(0.1511)
HOME IMPROVEMENT	-1.2291***	-0.6607***	-0.6581***
	(0.1590)	(0.1646)	(0.1647)
INVESTMENT	-0.8396***	-0.6688***	-0.6733***
	(0.2321)	(0.2354)	(0.2355)
MAJOR EVENT	-0.6049***	-0.4438***	-0.4400***
	(0.1570)	(0.1612)	(0.1614)
MAJOR PURCHASE	-0.5812***	-0.4397**	-0.4353**
	(0.1868)	(0.1904)	(0.1905)
OTHER CONSUMER LOANS	-0.6546***	-0.4664***	-0.4662***
	(0.1603)	(0.1646)	(0.1647)
PROFESSIONAL SERVICES	-0.2360	0.1966	0.2000
	(0.1511)	(0.1551)	(0.1553)
RENEWABLE ENERGY	-3.5601***	-2.9376***	-2.9418***
	(0.2525)	(0.2614)	(0.2615)
SOLAR BATTERY	-3.3106***	-2.7228***	-2.8038***
	(0.5280)	(0.5311)	(0.5362)
SOLAR ENERGY BATTERY	-3.7957***	-3.0625***	-3.0836***
	(1.0150)	(1.0162)	(1.0164)
SOLAR ENERGY EQUIPMENT	-2.5339***	-1.8641***	-1.9263***
	(0.5990)	(0.6011)	(0.6014)
SOLAR ENERGY PANELS	-2.3387***	-1.6443***	-1.6431***
	(0.2142)	(0.2196)	(0.2195)
Employment status			
EMPLOYED FULL TIME		-0.1667	-0.1714
		(0.1686)	(0.1687)
EMPLOYED PART TIME		0.0146	0.0071
		(0.1797)	(0.1799)
HOUSEPERSON		0.4336	0.4510
		(0.6267)	(0.6270)
RETIERD/OTHER		-0.0606	-0.0538
		(0.2577)	(0.2579)
SELF-EMPLOYED		0.5236***	0.5246***
		(0.1818)	(0.1820)
BORROWER INCOME		0.0587**	0.0581**
		(0.0266)	(0.0266)
Home ownership status			
OWN A HOME (No mortgage)		-0.2601**	-0.2481**
		(0.1211)	(0.1213)

TENANT (Mortgage)		0.1626 (0.1000)	0.1661* (0.1001)
TENANT (No mortgage)		0.7687*** (0.0511)	0.7840*** (0.0515)
Residence			
NSW			0.3629* (0.1888)
NT			0.6090** (0.2510)
QLD			0.3397* (0.1894)
SA			0.4765** (0.2052)
TAS			0.5532** (0.2561)
VIC			0.3162* (0.1898)
WA			0.5494*** (0.1925)
LR CHI2	916.1153	1252.8799	1273.9429
PROB > CHI2	0.0000	0.0000	0.0000
PSEUDO-R-SQUARED	0.0460	0.0629	0.0640
N	49928.0000	49928.0000	49928.0000

Potential problem with our sample database is the heterogeneous distribution of loans with a clear ending resolution. Around 50% of our database consists of loans with clear ending resolution (resolved loans). The share of resolved loans shrinks from around 96% in 2015 to 6% in 2020[3]. This potentially creates an issue of the sample selection as the loans included in the earlier periods may be misrepresenting defaulted loans. These loans might be affected by certain favourable economic environment or other time specific factors.

To address this issue of sample selection, we employ three different procedures after running baseline regressions. Firstly, we restrict the dataset into the subsample consisting of only the loans with clear ending resolution (resolved loans). We run the baseline regression on this restricted sample. Secondly, we apply a Heckman-type correction (1979) for sample selection. We use a binary dependent variable equal to 1 if the loan is "resolved" having a clear outcome and 0 otherwise. The selection in the sample is instrumentalised with loan-specific variables including the early payment dummy and borrower age. Thirdly, we estimate an ordered logit model in which the dependent variable is the status of the loans. Accordingly, the dependent variable (LOANSTATUS) takes one of the 6 values[4]. The results are reported in three panels of Table 5. The results are generally robust to three modifications with all estimation results being similar to the ones reported in baseline regression. We conclude that the detected impacts of inflation and stock market index are almost not affected by the selecting mechanism to construct our sample.

[3] The full breakdown of resolved and unresolved loans by each year is provided in Appendix A.
[4] In ordered logit model loans are classified as: Repaid, On schedule, less than 30 days late, more than 30 days late, Hardship and In default.

Table 5. The impact of inflation and stock market index to the probability of default: Testing for sample selection

Note: Table 5 presents the results of robustness checks for sample selection based on three panels. Panel A reports the results for logit regression analysis for the likelihood of loan default (DEFAULT) with the sample consisting of only resolved loans. Panel B reports the results after the application of the Heckman selection model, where the selection in the sample is instrumentalised with loan and borrower specific variables. Results are for logit regression analysis for the loan default (DEFAULT). Panel C results are for ordered logit regression analysis for the loan status (LOANSTATUS) with the 6 different loan outcomes. All model specifications employ robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01)

	(1)	(2)
Panel A: Resolved loans sample		
	DEFAULT	**DEFAULT**
CPI	0.1100***	
	(0.0154)	
INDEX		3.1511***
		(0.4950)
LR chi2	674.9600	664.1065
Prob > chi2	0.0000	0.0000
Pseudo-R-squared	0.0621	0.0611
N	25100.0000	25100.0000
Panel B: Heckman selection model		
	DEFAULT	**DEFAULT**
CPI	0.0138***	
	(0.0007)	
INDEX		0.3596***
		(0.0228)
LR chi2	1935.8145	1885.8409
Prob > chi2	0.0000	0.0000
N selected	25216.0000	25216.0000
Panel C: Ordered logit model		
	LOANSTATUS	**LOANSTATUS**
CPI	0.5100***	
	(0.0063)	
INDEX		7.2265***
		(0.3332)
LR chi2	1656.5755	1643.9957
Prob > chi2	0.0000	0.0000
Pseudo-R-squared	0.0635	0.0600
N	24712.0000	24712.0000

5. Conclusion

This study tested the effect of inflation and stock market index on P2P loan defaults. We used the loan book dataset by RateSetter Australia. As it has been indicated in the literature review section of the paper existing literature largely lacks empirical studies on selected topic. Therefore, we find it extremely difficult to compare the findings with earlier studies and highly limited the conclusions of the study.

Specifically, we found that the stock market index has significant positive impact on defaults. Buchak et al. (2018); Thakor (2020) proposed that at places where the traditional lending channels are not developed alternative investments prosper. However, none of the existing studies considered a direct link between stock market development and P2P lending. In this study, regression model with logistic regression method yielded significant coefficient for the variable of stock market index.

However, estimations based on logistic regression modelling yielded insignificant coefficients for inflation. Existing literature on P2P lending does not provide enough evidence with regards to the relationship of these two variables. Accordingly, we conclude that the relationship does not exist between these variables.

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