SELECTION EFFECTS OF LENDER AND BORROWER CHOICES ON RISK MEASUREMENT, MANAGEMENT AND PRUDENTIAL REGULATION

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Thi Mai Luong, declare that this thesis is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in the Finance Discipline Group at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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ABSTRACT

Empirical studies rely on features of observed data to gain new knowledge. However, data sets are often subject to selection bias. Recently, researchers have paid more attention to the impact of sample selection bias on outcome processes. In banking, selection is based on both lender and consumer choices and significantly affects outcomes of risk performance. This thesis presents three studies on the selection effects of lender and borrower choices on risk measurement, management and prudential regulation.

The first study investigates the voluntary selection of banks to participate in a government guarantee scheme implemented during Global Financial Crisis 2008 – 2009 in Australia. First, we find strong empirical evidence that Australian banks that entered into the wholesale funding guarantee scheme offered by the Australian Government experienced a significant reduction in their funding costs and funding premiums. However, we also show that the subsequent removal of the guarantee scheme did not result in a full repricing of funding costs to normal levels. Further, the guarantee program did not cause excessive risk taking in terms of general bank risk, asset risk, or liquidity risk. Additionally, banks allocated the additional debt funding to residential mortgage loans coincided with a period of strong growth in house prices in Australia. The findings contribute to bank risk management on the liability side.

The second study investigates the impact of prepayment selection on default likelihood. First, we document that prepayment and default are linked in a u-shaped pattern. Default risk is high for two distinct groups. The first group includes borrowers who have low prepayment risk as suggested by observed factors (unconditional effect). The second group includes borrowers who have high prepayment risk but did not refinance and remain in the sample post prepayment (selection effect). Second, the main cause for a high default rate in upturns is a

selection effect, while that for high default in downturns is an unconditional effect. Third, industry practice models result in a significant error in default calibration. We propose a two-stage model with a novel correction term to achieve a better default prediction than industry and literature models. The findings contribute to bank risk measurement and management on the lending side.

The third study explores two approaches to predict prepayment risk and default risk in the multi-period setting: a life-cycle model and a forward model. Using data of US fixed-rate prime mortgages from 2000–2016, we find that both models perform equally well for prepayment and default predictions in the first three years, while the accuracy of both models decreases for longer periods. A life-cycle model provides a better calibration for later ages, while a forward model is more accurate in forecasts for periods beyond three years. We analyze the impact of prepayment selection on multi-period default predictions. We find that a default model, which controls for prepayment selection, provides more accurate default probabilities in long run than a model without selection. The mean absolute error can reduce by nearly 50% if controlling for prepayment selection. Our findings are useful for banks to assess more accurately mortgage risk over the loan lifetime and to implement loan loss provisioning changes under international accounting standards

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LIST OF ABBREVIATIONS

ADI	Authorised deposit-taking institution
AFT	Accelerated failure time
APRA	Australian Prudential Regulation Authority
AUROC	Area under receiver operating curve
CCR	Credit correction ratio
CDF	Cumulative distribution function
CPH	Cox proportional hazards
DTI	Debt-to-income
GFC	Global Financial Crisis
HPI	House price index
IFRS 9	International Financial Reporting Standard 9
IMR	Inverse Mills Ratio
LTV	Loan-to-value
LIBOR	London Inter-bank Offered Rate
MAE	Mean absolute error
MNL	Multinomial logit
PD	Probability of default
PP	Probability of prepayment
US GAAP	United States Generally Accepted Accounting Principles
WGS	Wholesale Government Guarantee Scheme

Chapter 1: Introduction

1.1 Motivation

Empirical studies rely on features of observed data to gain new knowledge. However, data are often subject to selection bias and do not accurately represent a target population. This issue arises due to the data collection process being subject to the decisions of data collectors or participants. Recently, researchers have paid more attention to the impact of sample selection bias on outcome processes and methods to correct this bias.

Selection can be divided into three types. First, inclusion selection is when subjects/individuals are entered into the sample. Participants are selected via screening selection or voluntary selection (self-selection). Second, exclusion selection is when some groups choose to leave the sample. Third, survivorship selection requires subjects/individuals that pass the survival process to be included in the data. For panel data, subjects are observed in multiple periods. Exit events are payoff, default and maturity. Subjects are no longer observed in the periods following an exit event. Payoff is subject to borrower choice and driven by an independent random process that is correlated with the default process and hence informative to the default process. Specifying the payoff process using econometric techniques provides for a better default prediction and reduces biases caused by time-varying changes of the payoff process.

These three selection types imply that only part of the data are observable post selection, with the main difference being in how participants are selected. In most cases, selection processes result in biases for parameter estimates, true treatment effects and predicted outcomes of models. These biases can lead to incorrect interpretations and alter the findings.

Table 1.1 Literature of sample selection process

Panel A includes studies of sample selection by lender choices and Panel B includes studies of sample selection by consumer choices.

Study	Selection process	Selection type	Outcome process	Correction techniques	Data	Country
Panel A: Selection processes utilizing lender choices						
Lim, Minton and Weisbach (2014)	Loan approval	Inclusion	Loan pricing	Two-stage Heckman	2006–2009	Europe
Marshall, Tang and Milne (2010)	Loan approval	Inclusion	Default	Two-stage Heckman	1995–2003	UK
Craig and Hardee (2007)	Loan approval	Inclusion	Credit availability	Two-stage Heckman	1998	US
Roszbach (2004)	Loan approval	Inclusion	Survival time of loan	Bivariate Tobit	1994–1995	Sweden
Jacobson and Roszbach (2003)	Loan approval	Inclusion	Value-at-risk	Bivariate Probit	1994–1995	Sweden
Banasik, Crook and Thomas (2003)	Loan approval	Inclusion	Default	Bivariate Probit	Simulated data	
Ross (2000)	Loan approval	Inclusion	Default	Two-stage Heckman	1986–1992	US
De Haas, Ferreira and Taci (2010)	Bank participation	Inclusion	Portfolio composition	Two-stage Heckman	2004	Global
Ashraf, Altunbas and Goddard (2007)	Bank participation	Inclusion	Credit derivatives volume	Two-stage Heckman	1997–2004	US
Linzert, Nautz and Bindseil (2007)	Bank participation	Inclusion	Bidding volume and rates	Two-stage Heckman	1999–2003	Europe
Angkinand (2009)	Bank participation	Inclusion	Cost of banking crises	Two-stage Heckman	1970–2003	Global
Poon and Frith (2005)	Bank participation	Inclusion	Credit rating	Two-stage Heckman	1999–2002	Global
Covitz, Hancock and Kwast (2004)	Bank participation	Inclusion	Credit spreads	Two-stage Heckman	1985–2002	US
Panel B: Selection processes utilizing consumer choices						
Dungey, Tchatoka and Yanotti (2018)	Loan product choice	Inclusion	Loan rate	Two-stage Heckman	2003–2008	Australia
Bourassa and Yin (2006)	Loan product choice	Inclusion	Ownership rate	Two-stage Heckman	1989–1990	Australia/US
Booth and Booth (2006)	Collateral choice	Inclusion	Borrowing costs	Two-stage Heckman	1987–1989	US
Lin et al. (2009)	Default	Inclusion	Property value	Two-stage Heckman	1990–2006	US
Pennington-Cross (2010)	Prepayment	Exclusion	Default	Multinomial Logit	2001–2005	US
Agarwal, Chang and Yavas (2012)	Prepayment	Exclusion	Default	Multinomial Logit	2004–2007	US
Bellotti and Crook (2013)	Default of credit cards	Survivorship	Default of credit cards	Life-cycle model	1999–2006	UK
Djeundje and Crook (2019)	Default of credit cards	Survivorship	Default of credit cards	Life-cycle model	1996–1997	US

Note. UK = United Kingdom, US = United States.

In banking, selection is based on both lender and consumer choices and significantly affects outcomes of risk performance. Table 1.1 summarizes the literature on sample selection bias in the field of banking.

In Panel A, two selection processes utilizing lender choices are the loan approval process and bank participation. The loan approval process describes a screening selection undertaken by lenders to choose low credit risk applicants and reject high credit risk applicants. This acceptance/rejection process results in a sample data of accepted borrowers only and, thus, may be biased in reflecting the population of all prospective borrowers. The bank participation process is a voluntary selection in which banks decide to take up a program or be included in the treatment group. These two selection processes are inclusion selection by which subjects are included in the sample non-randomly and observed in the following outcome process. To correct the selection bias, the two-stage Heckman model (1979) and a bivariate Probit/Tobit have been suggested.

In Panel B, there are various selection processes utilizing consumer choices — loan product choices (e.g., between a fixed-rate and variable-rate mortgage), pledging collaterals, and prepayment. Of these choices, prepayment is unique in being an exclusion selection; that is, borrowers leave the sample and are no longer observed. This type of selection results in a loss of observations/subjects in the following outcome process (e.g., default). The literature has considered prepayment and default as competing risks, not a selection mechanism, and often used a multinomial Logit (MNL) model to control for competing risks. Survivorship selection is often studied via a default process in which a life-cycle model is used to predict the default probabilities of credit cards over multiple periods. An alternative to multi-period forecasts is the forward models used in studies of corporate default.

This thesis presents three studies on the selection effects of lender and borrower choices on risk measurement, management and prudential regulation. Each study explores one type of selection process — inclusion, exclusion and survivorship — presented in Chapters 2, 3 and 4 respectively. Table 1.2 shows an alignment of three studies in this thesis in the bank risk management.

Table 1.2: Relationship of thesis chapters to bank activities

Chapter 2 is relevant to liabilities management. Chapter 3 and Chapter 4 study risk management on bank assets.

Chapter	Bank activities	Dependent variables	Time	Country
Chapter 2	Liabilities	• Bank funding costs • Bank risk taking	One-period	Australia
Chapter 3	Assets (mortgages)	• Prepayment • Default	One-period	US
Chapter 4	Assets (mortgages)	• Prepayment • Default	Multi-period	US

The first study investigates the voluntary selection of Australian banks to participate in an Australian Government guarantee scheme implemented during the 2008–2009 Global Financial Crisis (GFC). Selection bias arises because the banks may have had incentive to adopt voluntarily the scheme and the outcome process is only observed for participating banks. This study aims to measure the impact of the guarantee program on banks' funding costs and risk taking. We conduct a natural experiment using the difference-in-differences method and controls for voluntary adoption to quantify the true effect of the guarantee program. The findings contribute to bank risk management on the liability side.

The second study investigates the exclusion selection of borrowers who decide to prepay their mortgages before maturity and leave the bank's portfolio. Selection bias arises as low credit risk borrowers often prepay and high credit risk borrowers often default; thus, the outcome process of default is only known for borrowers who choose to stay. This study quantifies the effect of prepayment selection on the default likelihood of sample subgroups. We provide a method to correct this selection bias and achieve better accuracy of default prediction. The findings contribute to bank risk measurement and management on the lending side.

The third study investigates the survivorship selection of borrowers to prepay and default over multi-periods of mortgages. The outcome process observes the likelihood of prepayment and default in a multi-period setting that considers survivorship over time. Selection bias arises as once a loan is prepaid or defaulted it leaves the sample forever and is no longer observed in subsequent periods. The portfolio is subject to change depending on the probability that loans will exit sooner or later in future periods. This study compares two approaches to forecast multi-period prepayment and default probabilities: a life-cycle model and a forward model. A life-cycle model predicts a loan's life cycle based on the loan's position in its lifetime (associated with borrower life cycles). A forward model uses known data to predict different horizons. For each method, default model is conditional on prepayment selection. We find that the life-cycle approach with control for prepayment selection can improve the accuracy of default predictions in both the short and long run. The findings contribute to bank risk measurement and management on the lending side and implementation of the latest prudential regulations on lifetime expected losses (International Financial Reporting Standard 9 (IFRS 9) and the United States Generally Accepted Accounting Principles (US GAAP)).

Paper 2 investigates the impact of prepayments on defaults in the one-period setting, which means the exit of loans at a time affects default rates at the same time. Paper 3 employs the impact of prepayments in the multi-period setting. It shows to predict default risk in different horizons considering the dynamic change in payoff probabilities. Time-varying changes of the payoff process affect survival probabilities of loans over the lifetime.

The next section reviews the literature on selection effects in banking.

1.2 Literature review

1.2.1 Inclusion selection

Inclusion selection is the most commonly discussed selection process in the literature. In bank lending, loan approval is the most common process subject to inclusion selection. Lenders create a mechanism to select low risk applicants for the portfolio and then track the default status of those borrowers. A potential problem is that the models used to predict the probability of repayment of loan applicants are developed based only on the data of accepted applicants (low risk borrowers). Marshall, Tang and Milne (2010) provide evidence that the loan approval process (rejection or acceptance) is significantly correlated with the default process. There is a significant improvement in forecasting performance when taking into account sample selection bias.

Yezer, Phillips and Trost (1994) show that estimated coefficients of mortgage terms such as loan-to-value (LTV) ratio are subject to significant bias in both rejection and default equations. Greene (1998) shows that a model controlling for both rejected and accepted loan applicants predicts a much higher average default probability. Banasik and Crook (2007) also suggested that techniques incorporating a selection process can improve the predictive performance of default models.

Bank participation is also a type of selection. For example, Ashraf, Altunbas and Goddard (2007) develop a model for bank participation in credit derivative markets and, conditional on participation, the factors that determine the volume of business transacted. Angkinand (2009) analyze relationship between banking regulation and supervision and the severity of banking crises measured in terms of the magnitude of output loss. The paper corrects for the sample selection bias by including only countries that experienced banking crises. Poon and Frith (2005) analyze the bias in credit ratings of shadow group of firms that have not asked for a rating by credit rating agencies.

The literature often uses a two-stage Heckman (1979) model to control for the inclusion selection. The first stage is a selection regression and the second stage is an outcome regression. After the first stage, the Inverse Mills Ratio (IMR) is calculated and then included in the second stage as an independent variable controlling for the selection. Although the Heckman (1979) model is widely used, later work highlighted shortcomings in the method. Puhani (2000) shows that the results of the second stage may vary from the results in the first stage that are highly sensitive to the selected variables for inclusion. Puhani (2000) also documents that a Heckman (1979) model using IMR does not provide an improvement in predictive power relative to a direct regression on the selected sample.

To extend the literature on the effects of lender choices on risk management, the first study in this thesis (Chapter 2) investigates the selection of banks that volunteered to participate in an Australian Government guarantee scheme. This inclusion mechanism is different from the loan approval process as inclusion was the result of self-selection, rather than a screening process.

1.2.2 Exclusion selection

Exclusion selection is less studied in relation to finance and banking. The most common phenomenon in this selection process is prepayment. Once a loan is prepaid, it leaves the portfolio and is no longer observed in the default outcomes.

The literature often views prepayment and default as competing risks, with borrowers choosing either option. However, this perspective is problematic. Borrowers can choose to prepay or default if the utility of one option exceeds the other, but, while prepayment is a choice, default may not be. For example, borrowers will choose to prepay their existing mortgage to refinance a new mortgage if the incentive of prepayment is greater than its cost. Conversely, borrowers often do not actively choose to default. Further, the perspective of two competing risks considers all options as being explained by the same set of factors, while in reality some factors drive prepayment but not default.

An alternative method for viewing the competing risks of mortgage termination is the MNL model. Pennington-Cross (2010) models the multiple outcomes of a loan, such as prepayment, foreclosure, partial cure, and cure. Agarwal, Chang and Yavas (2012) find an adverse selection in securitization, in that securitized loans have a higher prepayment risk and lower default risk than loans on lenders' balance sheets. The studies compare the parameter estimates, but do not assess the calibration of model-implied probability of default (PD).

To add to the literature, the second study in this thesis (Chapter 3) investigates the impact of borrowers' choices to prepay on default likelihood. We propose a method to correct this selection bias that can be used in other selection areas that the literature has neglected, such as the removal of delisted companies and customer churn.

1.2.3 Survivorship selection

Survivorship selection is a special selection process in that it considers multi-period exclusion of subjects/individuals. The literature has developed a separate strand of survival analysis for survivorship. Common survival models are the Cox proportional hazards (CPH) model and accelerated failure time (AFT) model. Those models mainly deal with a survival process with a single "death event" (e.g., default). The applications of survival analysis are categorized according to the asset classes of personal loans (Stepanova and Thomas, 2002; Tong, Mues, and Thomas, 2012), credit cards (Gross and Souleles, 2002; Bellotti and Crook, 2009), and corporate bonds (Krüger et al., 2018). However, in bank lending, prepayment contributes significantly to the change of sample data over multiple periods, as 60% of loans are prepaid in the first 10 years despite a substantial tenor of 30 years.

Extensive work using a life-cycle (discrete time survival) model has been conducted on credit cards (e.g., Bellotti and Crook, 2013; Luo, Kong, and Nie, 2016; Djeundje and Crook, 2019). This approach uses Probit/Logit regressions and incorporates a function of age for the dynamic future forecasts. In comparing methods of survival analysis, Banasik, Crook and Thomas (1999) find that a life-cycle model is competitive in default forecast in the first year. Luo, Kong, and Nie (2016) find that the splines based discrete time survival model can improve prediction accuracy. Applications on mortgages are limited.

A third approach is a forward model that uses to predict probabilities in different horizons (e.g., Duan, Sun and Wang, 2012; Campbell, Hilscher and Szilagyi, 2008). These papers provide techniques to predict default risk in a multi-period setting, which may be applicable solutions when considering mortgage risk over the lifetime of loans.

Over the lifetime, mortgage risk is changing due to borrowers' positions in life or variations in risk factors (e.g. macroeconomy). As a multi-period forecast of risk factors is challenging, these models aim to predict future events based on observed information.

The forward models used in the papers are applied in predicting/modeling corporate credit risk. There is no existing paper applying similar techniques in consumer credit risk prediction.

To add to the literature, we apply the life-cycle model and forward model to mortgages. We also compare versions of default models with and without controlling for prepayment selection in multi-period forecasts. The aim is to find which method is more accurate in multi-period forecasting of mortgage risk.

1.3 Thesis contributions

Generally, this thesis contributes to the literature on bank risk measurement, management, and prudential regulations.

The first study contributes to the literature on understanding the impact of a wholesale guarantee scheme on liability risk management. First, we find strong empirical evidence that Australian banks that entered into the wholesale funding guarantee experienced a significant reduction in their funding costs and funding premiums. However, we also show that the subsequent removal of the guarantee scheme did not result in a full repricing of funding costs to normal levels. Further, the guarantee program did not cause excessive risk taking in terms of general bank risk, asset risk, or liquidity risk. Additionally, banks being allocated the additional debt funding to residential mortgage loans coincided with a period of strong growth in house prices in Australia.

The second study investigates the impact of prepayment selection on default likelihood. There are three main findings. First, we document that prepayment and default are linked in a u-shaped pattern. Relatively high default is likely to occur for two distinct groups. The first group includes borrowers who have low prepayment risk as suggested by observed factors (unconditional effect). The second group includes borrowers who have high prepayment risk but did not refinance and remain in the sample post prepayment (selection effect). Second, the main cause for a high default rate in upturns is a selection effect, while that for high default in downturns is an unconditional effect. Third, industry practice models result in a significant error in default calibration. We propose a two-stage model with a novel correction term to achieve a better default prediction than industry and literature models.

The third study contributes to the literature on using different approaches to predict mortgages in the long run. We find that both models perform equally well for prepayment and default predictions in the first three years. The accuracy of models becomes worse for longer periods. We find that a life-cycle model provides a better calibration for later ages, while a forward model is more accurate in forecasts for longer times. We analyze the impact of prepayment selection on multi-period default predictions. We find that a default model, which controls for prepayment selection, provides more accurate default probabilities in long run than without selection. The mean absolute error of the selection model can reduce by nearly 50% compared to the non-selection model. Our findings are useful for banks to more accurately assess mortgage risk over a mortgage's lifetime and implement loan loss provisioning changes under international accounting standards.

1.4 Thesis structure

The thesis consists of five chapters. Chapter 1 has presented the motivations for the study, undertaken a literature review, and stated the thesis's contributions.

Chapter 2 presents a study on the choice of Australian banks to participate in an Australian Government guarantee scheme. The study investigates the impact of the program's voluntary section of banks on the selected banks' funding costs and risk taking.

Chapter 3 presents a study on borrowers' choice to prepay their mortgages before maturity. The study analyzes the effects of prepayment selection on default likelihood and the accuracy of default models.

Chapter 4 presents a study on the selection effects of borrowers to prepay or default over the lifetime of mortgages. The study provides the approaches to predict mortgage risk in multi-period setting.

Chapter 5 presents the thesis's conclusions, summarizing the key findings and implications from the three studies for industry practice and regulators.

Chapter 2: The Impact of Government Wholesale Guarantees on Banks' Funding Costs and Lending Behavior: Evidence from a Natural Experiment [1]

2.1 Abstract

This study compares the effects of the introduction and subsequent removal of a unique government Wholesale Funding Guarantee Scheme (WGS) in Australia on the funding costs and loan growth of authorised deposit-taking institutions (ADIs). Our identification strategy exploits the voluntary adoption of the WGS by ADIs using a difference-in-differences estimation approach. We find strong causal evidence to indicate that the government guarantee helped large ADIs to reduce their funding costs relatively more than for smaller ADIs. Furthermore, large ADIs continued to benefit from the WGS beyond the official removal of the government guarantee due to market perceptions of continued implicit government support for the too-big-to-fail banks. We also find that the guarantee encouraged large banks to shift their loan portfolios into housing loans thereby reducing their riskiness. Further tests using guaranteed and non-guaranteed bonds issued by ADIs show that the largest banks experienced a net reduction of 6.2 bps from adopting the government guarantee.

2.2 Introduction

Government interventions and support of the banking sector has been the subject of much public debate since the 2007-2008 Global Financial Crisis (GFC). The potential adverse consequences of government support for banks and the sovereign-bank nexus are well

[1] This chapter has been published in *Pacific-Basin Finance Journal.*

documented in the recent literature (Acharya, Drechsler and Schnabl, 2014; Dam and Koetter, 2012; Duchin and Sosyura, 2014; Gropp, Gruendl and Guettler, 2013; Hryckiewicz, 2014). The evidence focuses on government support in the form of bailouts and government protection of bank deposits. In contrast, the impact of government guarantees on banks' wholesale debt funding costs and risk-taking behaviour is less understood due to limitations of bank level data.[2] This paper accesses a unique dataset from Australia and aims to fill this void by examining the direct impact of the provision of an explicit guarantee by the Australian Government on deposit taking institutions' wholesale debt funding during the height of the GFC.

In recent years, governments in a number of countries around the world have strengthened deposit protection arrangements and introduced explicit guarantees for financial institutions' wholesale debt. Wholesale funding guarantee schemes have been implemented in response to the extremely difficult funding conditions experienced during the GFC. The schemes are designed to promote financial system stability and to encourage the ongoing provision of credit, by supporting confidence in the financial sector, reducing actual and perceived risks and assisting financial institutions to access wholesale funding (at a reasonable cost) during a time of considerable financial turbulence. Unlike the Financial Claims Scheme which was introduced to protect retail deposits up to AUD 1 million, the Australian Government Wholesale Funding Guarantee Scheme (WGS) covered large deposits greater than AUD 1 million, as well as, wholesale debt funding used by Australian deposit-taking institutions up to maturities of five years. The WGS commenced on 28 November 2008 at the height of the GFC and closed on the 31 March 2010. The government guarantee provided was unique in that Australia did not previously have any explicit deposit protection, the scheme was voluntary, and unlike other government guarantees offered, there was initially no explicit end date announced for the scheme. This signalled to market participants that the government was

[2] A notable exception is the prior work of Gropp, Gruendl and Guettler (2013) studying the removal of a government guarantee for German savings banks and the subsequent reduction in bank risk.

prepared to support the banks for 'as long as it takes'. This offers a rare natural experiment for understanding the causal effects of government guarantees on bank funding costs and lending behaviour.

Our study not only bridges but also extends the two separate strands of the banking literature - on the determinants of bank funding costs and the impact of the provision of a financial safety net on market discipline. For example, Demirguc-Kunt and Huizinga (2004), Imai (2006), Yan et al. (2014), Hadad et al. (2011), Karas et al. (2013), all find that the introduction of a domestic deposit insurance scheme lowers the perceived risks for financial institutions and this, in turn, leads to a reduction in market discipline by depositors for protected banks. This reduces the interest rates demanded by depositors resulting in a major reduction in funding costs for financial institutions.

However, going forward, banks worldwide may become increasingly less reliant on traditional deposit funding for two main reasons. First, the new Basel III liquidity rules incentivise banks to use more long-term wholesale funding to better match the maturity structures in their typical uses of funds for extending longer-term loans.[3] Second, as investors chase higher yields in an historically low interest rate environment they tend to have a stronger preference to invest their funds in longer term debt securities offered by financial institutions over deposits. Hence, it is important to understand the unintended distortionary effects of wholesale funding guarantees provided by governments. It is possible that guarantees on wholesale funding may pose an even greater moral hazard concern, given that the monitoring of banks by sophisticated creditors in the wholesale funding markets is likely to be more effective than that provided by individual retail depositors. Furthermore, Boyle et al. (2015) provide evidence based on survey responses to show that there is actually greater withdrawal

[3] Basel III liquidity standards require banks to have net stable funding ratios (NSFR) above 100% to ensure that the liquidity mismatches between banks' assets and liabilities are significantly reduced and they become more resilient in times of liquidity shortages, such as during the GFC (see King (2013) for details on this measure).

risk for deposits when countries, without prior explicit deposit insurance, introduce deposit insurance schemes during banking crises, which was the case in Australia. Market discipline and bank risk taking are inversely related; especially post GFC (Hoang, Raff and Haq, 2014; and Haq et al., 2014).

Australia offers a unique setting to study the impact of the introduction of a wholesale funding guarantee scheme as, up until recently, it was one of only two OECD countries with neither an explicit deposit nor wholesale funding guarantee scheme (New Zealand being the other). We exploit the cross-sectional as well as time-series variation provided by the introduction of the voluntary WGS. ADIs that chose to participate in the WGS had to pay a risk-based fee priced between 70 and 150 basis points depending on their credit rating. The maximum fee of 150 basis points applied to ADIs which were rated BBB+ or below, as well as for unrated ADIs. Furthermore, unlike almost every other developed country, different types of deposit-taking institutions – banks, credit unions and building societies in Australia are all covered and supervised by the same regulator, the Australian Prudential Regulation Authority (APRA) and are all subject to the same prudential and legislative requirements. For this reason, Australia affords a rare, natural experiment for an empirical comparison on the impact of both the adoption and removal of a wholesale funding guarantee scheme on various financial intermediaries' funding costs.

In the context of the Financial Claims Scheme introduced in Australia for retail deposits during the GFC, Yan et al. (2014) showed that market deposit rates and deposit growth for ADIs became much less sensitive to bank fundamentals, once the scheme was in place. Yan et al. (2015) show weakening market discipline for credit unions post GFC.

However, in contrast, relatively little is known about the effects of the WGS on different types of ADIs with heterogeneous funding and ownership structures. To date, there has been a dearth of attention paid to the effect of government guarantees on mutuals, such as credit unions and building societies. Moreover, there has also been no previous study on the effect of introducing a wholesale funding guarantee without any prior deposit insurance already in place nor the exogenous removal of a wholesale funding guarantee scheme after its implementation. Our paper aims to fill these voids in the literature by comparing the effects of the recent introduction of the WGS on commercial banks and mutuals (credit unions and building societies). Our study differs from existing studies on deposit insurance, in that we focus on the effects of explicitly insuring wholesale debt and large-sized deposits.

To establish causality, we use a difference-in-differences approach on a total sample of 15 Australian banks, 13 building societies and 132 credit unions, reporting to the prudential regulator, APRA. We find strong empirical evidence to indicate that ADIs in general, experienced a significant reduction in their funding costs and funding premiums after taking up the WGS. The removal of the guarantee scheme had no effect on the funding costs and funding premiums for all types of ADIs suggesting that the guaranteed ADIs continued to benefit from market perceptions of implicit government support beyond the guarantee scheme. Following WGS adoption, we find that asset risk reduced significantly.

There are important policy implications emanating from our findings as policy makers need to be mindful of the moral hazard problems associated with offering government guarantees on banks' funding sources to maintain credit provision even in times of stress. There is some evidence to suggest that, had the government guarantee been kept in place for a prolonged period of time, banks could have been perversely incentivised to become highly levered. Instead guaranteed banks shifted their loan portfolios towards household mortgages.

The remainder of the chapter is structured as follows: in Section 2.3 we provide some background into the Australian financial institutions assessed in this paper as well as the Australian Wholesale Funding Guarantee scheme. Section 2.4 outlines and reviews the related literature. Section 2.5 presents the data and methodology used. Section 2.6 reports the main empirical results and robustness checks. Section 2.7 discusses our findings and concludes.

2.3 Background

2.3.1 Australian banking sector

The banking sector in Australia is highly concentrated, with four major banks ("the big four") accounting for approximately 88 per cent of all domestic bank assets as of 2014. Apart from the major commercial banks, the banking system also comprises various "other banks" that in the past have had a local concentration in one state or territory. These banks account for approximately ten per cent of all domestic bank assets.[4] Additionally, there are two other categories of ADIs – credit unions and building societies. When combined together, they account for approximately two per cent of all bank assets. Credit Unions and Building Societies (also known as mutuals), unlike larger deposit-taking institutions, traditionally focus primarily on retail banking and are still a pivotal source of competition within the retail banking sector. Mutuals differ from commercial banks in that their customers have some ownership in the financial institution. They are not publicly listed companies and are limited in their ability to issue new shareholder equity. Thus, they rely to a greater extent on retained earnings to generate new capital. This differs from publicly listed commercial banks, which can issue new shares to raise extra capital (Rasmussen, 1988). In Australia, mutuals come under the same legislative and prudential requirements as all other Australian banks.

We exclude foreign branches and subsidiaries in this study as these rely on funding by parent companies overseas as well as transfer costing rendering these ADIs to be incomparable to local ADIs for the purpose of our study.

[4] These numbers emanate from our empirical analysis.

2.3.2 Wholesale Funding Guarantee Scheme

The Australian Government Guarantee Scheme for deposits greater than AUD 1 million and wholesale funding (WGS), was announced in October 2008 and commenced on 28 November in that year.[5] It was introduced in response to the evaporation of liquidity in the global financial system. The scheme was designed to restore financial system stability in Australia and to encourage the ongoing provision of credit by supporting confidence and assisting ADIs to access wholesale funding from international credit markets at a reasonable cost during the time of considerable turbulence and liquidity shortage. The scheme also ensured that Australian institutions were not placed at a disadvantage, compared to their international competitors, who could access similar government guarantees on bank debt. The scheme was administered by the national central bank (the Reserve Bank of Australia) for the federal government. Eligible ADIs were able to apply to having their eligible wholesale funding securities guaranteed under the scheme. The scheme was voluntary and subject to an approval process and the payment of a monthly fee by the ADI on the amounts guaranteed. Following improvements in funding and market conditions, the Australian government closed the wholesale funding guarantee to new borrowings on 31st of March 2010.

Figure 2.1 shows the number of ADIs taking up the WGS and amounts guaranteed by the program until maturity from our data. Total assets and total wholesale funds of all ADIs during the guarantee period were 2 trillion AUD and 800 billion AUD, respectively. Maximum amounts insured by the WGS was 500 billion AUD, accounting for 25% of total assets and 62% of total wholesale funds.

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[5] See http://www.guaranteescheme.gov.au/

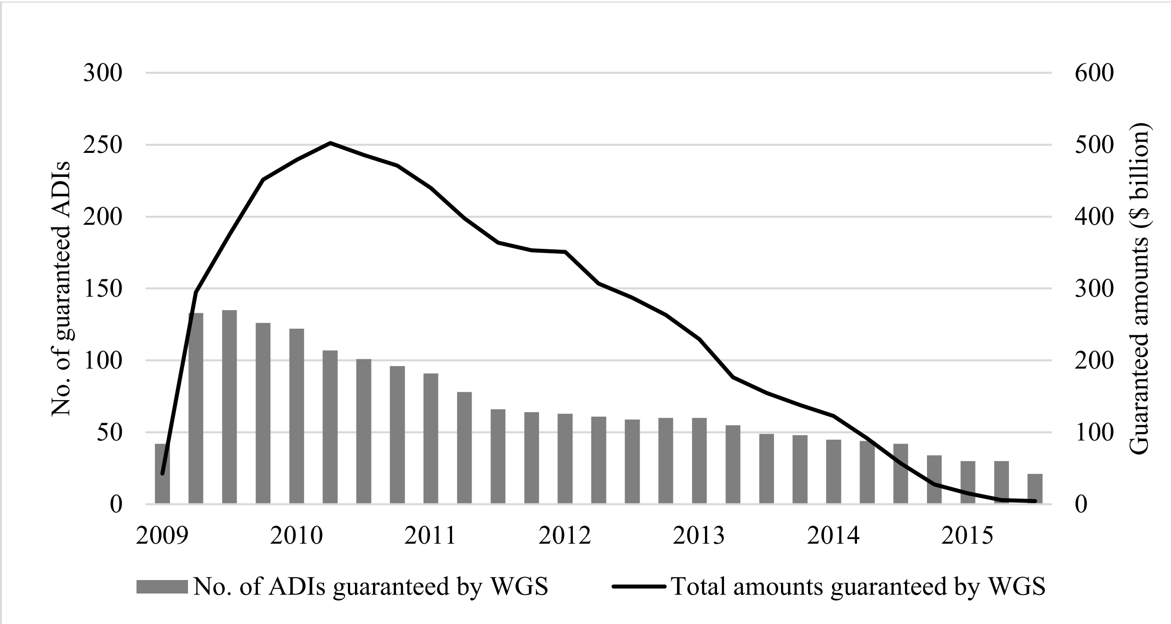

Figure 2.1. WGS participation activities

This figure shows the number of guaranteed ADIs and guaranteed amounts by the WGS until maturity.

2.4 Literature review and research questions

2.4.1 Determinants of banks' funding costs and funding premiums

We contribute to the emerging literature on banks' funding costs that remains comparatively small and includes contributions by Deans and Stewart (2012), Araten and Turner (2013), Berkelmans and Duong (2014), Beau (2014), Babihuga and Spaltro (2014), Aymanns et al. (2016) and Cummings and Wright (2016). These papers examine a number of drivers on banks' funding costs and reveal that banks' asset quality, capital adequacy, funding liquidity, funding mix, and the general state of the macroeconomy matter.

Funding costs across financial institutions differ due to ADIs' access to wholesale debt markets. There can be various proxies for banks' funding costs. To measure funding costs, first we use the implicit interest rate on a bank's interest-bearing liabilities, i.e., total interest expenses divided by interest-bearing liabilities (Demirgüç-Kunt and Huizinga, 2004). Additionally, we also explicitly account for the dynamics in base-level funding costs within the economy by computing measures of banks' funding premium and also the funding costs on repriced interest-bearing liabilities.

Large ADIs can take advantage of their size, diversification and frequent security issuances to reduce their funding costs (Kroszner, 2016; and Aymanns et al., 2016). Beau (2014) analyses direct and indirect costs associated with the issuance of wholesale funding. Deans and Stewart (2012) show evidence for Australia that major banks have a higher proportion of wholesale debt compared to other banks while for credit unions and building societies, deposits make up the bulk of their funding structure. Therefore, the wholesale liabilities ratio is a key factor driving variations in funding costs across banks. Furthermore, Babihuga and Spaltro (2014) investigate marginal funding costs, defined as the sum of the LIBOR rate and bank credit spreads and find that macroeconomic variables account for much of the variations in bank funding costs.

In terms of funding premiums, which is a measure of the difference between overall funding costs and the cash rate (interest rate for short-term bank deposits with the Reserve Bank of Australia), Deans and Stewart (2012) show that during 2008 and the early part of 2009, funding premiums increase strongly as a result of the GFC. Berkelmans and Duong (2014) document that spreads between funding costs and cash rate narrow marginally after a crisis, reflecting the shifts in the composition of banks' funding liabilities and the narrowing of wholesale debt spreads. However, both studies are based on aggregate summary statistics rather than a bank-level analysis and it is not clear how government guarantees introduced around the world during the GFC have directly affected banks' funding costs.

To extend the current literature on bank funding costs we test the following hypotheses:

H1: Banks that utilised the Wholesale Funding Guarantee Scheme (WGS) experienced lower funding costs compared to ADIs that did not participate in the WGS.

H2: The removal of the WGS had less effect on banks' funding costs than its adoption due to a continued perceived level of implicit government support beyond the closure of the WGS.

2.4.2 Guarantees and bank risk-taking

Banks' shareholders are residual claimants. Equity is similar to a call-option on the asset value (with the debt value as the strike price). The value of the option increases with the variance of the underlying asset value and shareholders have hence an incentive to engage in high risk-taking activities to increase their residual claims at the expense of depositors' funds.

However, in mutual institutions, the depositors are also the shareholders. Hence, residual claims are offset by the decrease in fixed claims (interest paid on deposits) and the incentive for mutuals to take higher risk is lower than for non-mutuals. Furthermore, mutuals are also deterred from pursuing risky ventures by their limited capacity to raise new equity capital. They typically rely on retained earnings to generate capital. Thus, capital constraints impede risk-taking (Llewellen and Holmas, 1991).

The ability to raise capital from external capital markets gives banks a competitive advantage and in turn makes them more attractive to depositors. Recent banking theories suggest that there is a positive relationship between bank capital and market share (Mehran and Thakor, 2011). The evidence suggests that well-capitalised institutions are able to compete more effectively for deposits (Calomiris and Wilson, 2004). Berger and Bouwman (2013) find that high levels of capital enhance medium and large US banks' performance, in relation to their resilience (i.e., survival) and market share, primarily during banking crises. This is consistent with most theories predicting that capital enhances banks' survival probabilities. Banks typically argue that holding more capital jeopardises their performance and leads to less credit supply and loss of profit due to increased funding costs.

However, incentive based theories predict that higher capital should enhance bank profitability. Holding more capital will either strengthen bank incentives to monitor its relationship with borrowers or banks will attenuate assets that elevate the probability of a financial crisis such as risky commercial real-estate loans (Acharya et al., 2011; Allen, Carletti and Marquez, 2011; Baker and Wurgler, 2015; and Berger and Bouwman, 2013).

Deposit insurance and other guarantees may present a moral hazard problem. Prior studies show that deposit insurance schemes increase bank risk and also the likelihood of having a banking crisis (Demirgüç-Kunt and Detragiache, 2002; Barth, Caprio and Levine, 2004). Yet, it remains that deposit insurance is a cornerstone of many banking systems, because it helps to protect savers and prevent bank runs. However, it also provides banks with incentives for excessive risk-taking because, firstly, it weakens the market discipline carried out by creditors, and secondly, the deposit insurance premium is typically mispriced due to regulators' limited ability to assess risks and to charge risk-adjusted premiums.

Some studies provide more specific evidence. For example, Gropp and Vesala (2004) find for a sample of European banks that explicit deposit insurance reduced bank risk during the 1990s whilst Anginer et al. (2014) find for a global sample of banks that deposit insurance generally increases bank risk during normal times, but decreased bank risk during the crisis period from 2007-2009. Ioannidou and Penas (2010) analyze the effect of deposit insurance on banks' risk-taking behavior using Bolivian credit registry data and find that banks originate riskier loans without mitigation through collateral or maturities. In a similar vein, Gropp, Gruendl and Guettler (2013) study the removal of a government guarantee following a lawsuit and find a reduction in bank risk via a reduction in the origination of high risk loans suggesting that having a government guarantee in place encourages bank risk taking. Furthermore, Black, Stock and Yadav (2016) argue that government guaranteed bank bonds improve debt liquidity and default risk, consistent with a reduction in bank funding costs but they do not provide empirical evidence on the latter. Bollen et al. (2015) find that banks insured by the WGS experienced a reduction in both systematic and systemic risks. Hoang, Raff and Haq (2014) find that bank risk is positively correlated with bank capital.

To further extend this current literature on the effects of deposit insurance and government guarantees on bank debt we also test the following hypothesis:

H3: Banks allocated the cheaper debt funding towards growing their loan portfolios in the booming housing sector after they adopted the WGS.

2.5 Empirical framework

The decision to participate is voluntary and banks that chose to participate may have special characteristics. Hence, in order to control for this selection process, we implement a two stage model throughout. In a first stage, we model the probability to participate in the WGS and we compute the Inverse Mills Ratio (IMR). We control for the IMR in all of our second stage models and employ a difference-in-differences estimation approach to directly test our key hypotheses. All models are based on standard errors clustered at the bank level. Using a difference-in-differences estimation we can observe the impact on the “treated” (insured) ADIs before and after the implementation of the WGS treatment. All panel regressions in this study are estimated using Ordinary Least Squares (OLS).

2.5.1 Control for WGS selection

More formally, banks participate voluntarily in the WGS and we model the probability to participate in the WGS with a Probit model with standard errors, which are clustered at the bank level:

$$P(WGS_{it} = 1) = \phi(\vartheta X_{it}) \tag{1}$$

We compute the Inverse Mills Ratio as follows:

$$\mathrm{IMR_{it}} = \frac{\phi(\vartheta \mathrm{X_{it}})}{\Phi(\vartheta \mathrm{X_{it}})}, \tag{2}$$

With the marginal density function of the standard normal distribution $\phi(.)$ and the cumulative density function of the standard normal distribution $\Phi(.)$. X_{it} is a vector of bank characteristics determining individual bank's participation decision. We use a number of variables that can explain for the voluntary selection by ADIs, including the potential fee applied if banks decide to enter into the scheme, size of banks, funding structure (leverage and wholesale funding ratio) and the level of bank risk (risk-weighted assets ratio and liquidity ratio). We expect that fee applied will be a constraint for bank to participate in the WGS while large sized banks, those with high wholesale funding ratio or high risk are likely to take up the scheme.

In a second step, we include the Inverse Mills Ratio (IMR) as a control variable in the models testing our main hypotheses.

2.5.2 Test of the adoption of the WGS guarantee

The following difference-in-differences equations are formulated to test the Wholesale Funding Guarantee Scheme's (WGS) impact on ADIs' funding costs:

$$FundingCost_{it} = \alpha\left(WGS_{ij} * DuringGar_t\right) + \beta WGS_i + \gamma DuringGar_t + \delta X_{it} + \theta IMR + \tau B_i + \varepsilon_{it} \quad (3)$$

where i indicates the individual ADI and t indicates the time period. We test three distinct measures for bank funding costs (*FundingCost$_{it}$*): (i) the average funding costs as the ratio of interest expenses relative to total liabilities, (ii) the funding premiums as the difference between average funding costs and the cash rate (i.e., a proxy for the risk-free interest rate), and (iii) the rate sensitive funding costs as the ratio of incremental interest expenses paid on new liabilities to new liabilities.

WGS_{ij} is the vector of two dummy variables, *WGS_SMALL* and WGS_BIG that take the value of one for the small and large sized ADIs respectively that chose to take the guarantee and the value of zero for those that did not. In this case, we define *WGS_BIG* including four big banks in Australian banking system. *DURINGGAR* is a dummy variable that takes the value of one for the period during the guarantee (Nov 2008 - Mar 2010) and the value of zero for other periods. WGS_{ij}**DURINGGAR* is our difference-in-differences (DiD) operator that shows the effect of the guarantee on the insured ADIs after it was introduced. X_{it} is a vector of bank-specific and macroeconomic control variables (see Table 1 for details). *IMR* is the Inverse Mills Ratio from our first stage regression which is included to account for the selection bias created by banks' voluntary adoption of the WGS. B_i is the vector of bank fixed effects. In addition, $\alpha, \beta, \gamma, \delta, \theta$ and τ are the respective parameters that indicate the sensitivities of test and control variables with regard to the dependent variable.

2.5.3 Test of the removal of the WGS guarantee

As Australia has been the only country that has removed an existing wholesale funding guarantee without any prior explicit protection scheme in place prior to the 2007-2008 Global Financial Crisis, our identification strategy also exploits this quasi-natural experiment to assess the removal effect of the guarantee on ADIs' funding costs. We introduce the variable *REMOVALGAR* in the following model:

$$FundingCost_{it} = \alpha(WGS_i * RemovalGar_t) + \beta(WGS_i * DuringGar_t) + \gamma RemovalGar_t + \pi DuringGar_t + \vartheta WGS_i + \delta X_{it} + \theta IMR + \tau B_i + \varepsilon_{it} \quad (4)$$

The variable WGS_{ij} is the vector of two dummy variables, *WGS_SMALL* and *WGS_BIG* that take the value of one for small and big ADIs respectively that chose to take the guarantee and the value of zero for those that did not. The variable *REMOVALGAR* takes the value of one for the periods after the removal of the guarantee and the value of zero for the periods before and during the guarantee. The variable *REMOVALGAR* allows us to incorporate both the removal and adoption effects in a single regression. However, as *REMOVALGAR* is identical with the control for the timing of the Financial Claims Scheme (*FCS*) included in Equation (3), we have removed *FCS* from the list of control variables in this model specification. All other variables and their parameters in Equation (4) are identical to those in Equation (3).

2.5.4 Test of bank risk-taking

We test the risk-taking behaviour of banks using the following model:

$$RiskTaking_{it} = \alpha(WGS_{ij} * DuringGar_t) + \beta WGS_i + \gamma DuringGar_t + \delta X_{it} + \theta IMR + \tau B_i + \varepsilon_{it} \quad (5)$$

We apply three proxies for bank risk-taking commonly used in the banking literature: (i) *Z-score* computed as the ratio of the sum of the averaged return on assets (ROA) and the capital adequacy ratios (CAR) to the standard deviations of ROA over the past four quarters, (ii) write-off ratio (*Writeoff*) as the ratio of total write-off loan to net loans and (iii) risk weighted assets to net loans ratio (RWA_Loan). Other independent variables and their parameters in Equation (5) remain the same as in Equation (3).

We proxy for risk taking using the loan write-off ratio, which is the ratio of loan write-offs to total net loans and effectively captures the actual losses experienced by banks. Other commonly used bank risk proxies like loan loss provisions may be confounded with the adoption of the WGS as big banks' provisioning practices are based on their internal ratings-based (IRB) approach to credit risk and small banks on the standardised approach after the introduction of Basel II (January 2008, see Cummings and Durrani, 2016 for further details). Under the IRB approach, the occurrence of the GFC led to specific increases of loan loss provisions at the same time as the WGS. IRB banks are also WGS participants and this may cause confounding effects.

2.5.5 Test of the impact of the WGS on bank loan growth

We next examine loan growth within banks after their adoption of the WGS using the following DiD model specification:

$$LoanGrowth_{it} = \alpha\big(WGS_{ij} * DuringGar_t\big) + \beta WGS_i + \gamma DuringGar_t + \delta X_{it} + \theta IMR + \tau B_i + \varepsilon_{it} \quad (6)$$

In Equation (6), we test three distinct measures for loan growth: (i) the quarterly growth rate of housing loans, (ii) the quarterly growth rate of non-housing loans, and (iii) the quarterly growth rate of gross loans extended. In addition, $\alpha, \beta, \gamma, \delta, \theta, \mu, \rho, \tau$ are the respective parameters that indicate the sensitivities of test and control variables with regard to the dependent variable.

2.5.6 Robustness check: propensity score matching with bootstrapping

The significant challenge that we face in studying Australian banks is that the banking sector is highly concentrated and it is difficult to find a one-to-one match for the treated Australian banks in our sample, especially the four majors who all adopted the WGS. To deal with this, we employ a propensity score matching approach by IMR categories.

We use the following steps to find a propensity score matched subsample of ADIs:

1. IMR is categorised into five groups of equal numbers of observations using the result from Stage 1 of the selection model.
2. Take a random sample with an equal number of treated banks and control banks in each group. We choose the one-to-one matching by taking the minimum number of banks in each group.
3. Run difference-in-differences regressions for the subsample.

A subsample is selected randomly without replacement. Hence, we conduct a bootstrapping test to obtain the distribution of treatment effect estimates. The Steps 1 to 3 above are repeated 100 times to obtain 100 random subsamples of 23 treated and 23 control banks. The descriptive statistics (mean, SD, median, P5 and P95) of estimates and average p-value is reported for the various adoption, removal, risk taking and loan portfolio regression tests. An extension to this bootstrap with replacement showed consistent results, which are available on request.

As we have matched propensity scores on subsamples, we no longer distinguish treatment effect on big and small banks. Instead, in the regression tests in Equations (3)-(6), we replace *WGS_BIG* and *WGS_SMALL* by the dummy variable, WGS, that takes the value of 1 if banks took up the scheme and 0 otherwise. The treatment effect now is measured through the difference-in-differences estimators *WGS*DURINGGAR* or *WGS*REMOVALGAR*.

2.5.7 Robustness checks: bond yield spread analysis

As a robustness check, we analyse the impact of the WGS on the yield spreads of bonds issued by Australian banks.

In the first stage, we estimate the propensity of issuing a WGS guaranteed bond:

$$P(WGS_{it} = 1) = \phi(\delta X_{it}) \tag{7}$$

In the second stage, we control for the IMR and test the impact of WGS participation on the wholesale funding costs:

$$Yield\ Spread_{it} = \alpha(WGSBond_i) + \beta Period_t * + \gamma B_{it} + \delta X_{it} + \theta IMR + \varepsilon_{it} \tag{8}$$

In Equation (8), the funding costs are measured by the bond yield spreads as the differences between the mid-yields at issuance and the US treasury rates (as the bonds are denominated in USD) of equal maturity. The dummy variable WGS_BOND takes the value of one if bonds are guaranteed by the WGS and takes the value of zero otherwise. $Period_t$ is a vector of variables that indicate three different sub-periods: i) pre-guarantee, ii) during guarantee, and iii) post-guarantee regimes. B_{it} is a vector of bond-specific factors and X_{it} is a vector of bank-specific factors. Again, IMR is the Inverse Mills Ratio generated from the guaranteed bond selection model in Equation (7) following Equation (2). Note that contrary to the bank models presented in prior sections (i.e., panel data) we analyse bond origination data (i.e., cross-sectional data; one observation per bond) and are unable to apply a DiD model due to the existence of multi-collinearity.

2.6 Empirical results

2.6.1 Data

We analyse 164 ADIs (15 Australian banks and of these, there are four major banks with 88 per cent of all domestic banking assets, 13 building societies, and 132 credit unions). We use confidential data provided by APRA that have been submitted by ADIs to APRA at a quarterly frequency. The data used includes information from the banks' balance sheets and profit and loss statements and other filings to the prudential regulator (including interest rate sensitivity, mortgage origination patterns and risk-weighted assets). Information in relation to ADIs' specific balance sheet figures are mandatorily collected periodically and is more detailed than publicly available annual report data. There is also a greater cross-sectional consistency as the data submission is subject to APRA's reporting standards that are common to all ADIs and this effectively rules out any reporting bias.

The sample period that we study is from January 2008 to December 2011. This sample period is selected in this study to provide three quarters before the guarantee, six quarters during the guarantee and three quarters after the guarantee. We choose this period for the base test in order to capture recent trend of treatment and control group before the guarantee took place. We also lengthen the sample period up to two year prior the WGS and two year post the WGS and see that all the findings are consistent with results of the base test.

We identify the list of banks that participated in the WGS from the Reserve Bank of Australia. In this paper, we analyse all ADIs in a pooled sample regression with consideration of participation rate by different ADIs during the guarantee period. There were 14 (out of 15 i.e. 93%) Australian banks that chose to adopt the WGS whilst 36% and 18% of building societies and credit unions adopted the WGS respectively. We are unable to run subsample regressions for the dominant four major banks individually as they all made use of the wholesale funding guarantee, rendering no suitable control group but we analyse treatment effects for those by introducing a separate variable, *WGS_BIG*.[6]

Furthermore, we analyse the economic rationale for guaranteeing bond issuances in a robustness check by analysing the yields to maturity at origination of bonds issued before and during the WGS. We map Moody's credit rating for each ADI at the time of WGS participation to the risk-based fee that ADIs had to pay for coverage under the WGS. The fee for ADIs to have their wholesale funds insured under the WGS was 70 basis points for ADIs rated AA- or higher, 100 basis points for ADIs rated between A- and A+, and 150 basis points for ADIs rated BBB+ or below, as well as for unrated ADIs (RBA, 2009). Table 2.1 provides the definitions of all the variables used in this study.

[6] As the potential impact of the WGS would depend on the extent to which ADIs relied on the scheme, we have tested the maximum amount of the wholesale liabilities that was covered for each ADI (relative to their total assets) as a measure of their wholesale funding guarantee utilisation by replacing the WGS dummy variable with the utilisation ratio. The utilisation ratio is the ratio of guaranteed liabilities to total liabilities (i.e., bounded between zero and one).The results are comparable to the WGS dummy.

Table 2.1 Definition of variables

This table provides the definitions of variables used for dependent variables (Panel A), test variables (Panel B) and control variables (Panel C).

Variable name	Definition	Data source
Panel A: Dependent variables		
AVGFUNDCOST	Average funding cost measured as a ratio of interest expense relative to total liabilities.	APRA
FUNDPREMIUM	Funding premium measured as the difference between average funding costs and cash rate.	APRA
RSFC	Rate sensitive funding cost measured as a ratio of incremental interest expense paid on new liabilities to new liabilities.	APRA
LEVERAGE	A ratio of total liabilities to total assets.	APRA
Z-SCORE	Natural logarithms of a ratio of summation between 4-quarter average return on assets (ROA) and capital adequacy ratio (CAR) to standard deviation of ROA.	APRA
WRTIE-OFF	A ratio of write-off loan to net loans.	APRA
RWA_LOAN	A ratio of risk weighted assets to net loans.	APRA
HOUSINGGR	Quarterly growth rate of housing loans.	APRA
NONHOUSINGGR	Quarterly growth rate of non-housing loans.	APRA
TOTALLOANGR	Quarterly growth rate of gross loans.	APRA
YIELDSPREAD	The difference between mid yield at issuance and the US treasury rate.	Bloomberg
Panel B: Test variables		
WGS	A dummy variable that takes the value of one for all ADIs that chose to take the guarantee and the value of zero for the ADIs that did not.	APRA
WGS_SMALL	A dummy variable that takes the value of one for the small ADIs that chose to take the guarantee and the value of zero for the ADIs that did not.	APRA
WGS_BIG	A dummy variable that takes the value of one for the four major ADIs that chose to take the guarantee and the value of zero for the ADIs that did not.	APRA
WGS_BOND	A dummy variable that takes value of one for bonds guaranteed by the WGS and takes value of zero if otherwise.	Bloomberg, RBA
DURINGGAR	A dummy variable that takes the value of one for the period during guarantee (Nov 2008 - Mar 2010) and the value of zero for other periods.	APRA
REMOVALGAR	A dummy variable that takes the value of one for the period of closing the WGS, and the value of zero for before and during the WGS.	APRA
PREGAR	A dummy variable that takes value of one for period of March 2008 - Dec 2008 (three quarters before introduction of guarantee scheme) and takes value of zero if otherwise.	Bloomberg
POSTGAR	A dummy variable that takes value of one for period of Mar 2010 - December 2010 (three quarters after closing guarantee scheme) and takes value of zero if otherwise.	Bloomberg
Panel C: Control variables		
FCS	A dummy variable that takes value of one for period of Financial Claim Scheme for retail deposit since Oct 2008 and takes value of zero if otherwise.	APRA
CAR	Capital adequacy ratio measured as the eligible Tier 1 and Tier 2 capital to total risk-weighted assets.	APRA
LAR	A ratio of cash and liquid assets relative to total assets.	APRA

LLR	Annualised loan loss rate computed as the provision for bad and doubtful debts relative to total assets.	APRA
WLR	The ratio of wholesale liabilities relative to total liabilities.	APRA
SIZE	Natural logarithms of total assets.	APRA
RWA	A ratio of risk weighted assets to total assets.	APRA
FEE_APPLIED	Potential fee applied for banks if those decided to take up the scheme.	APRA
BIDASKSPREAD	The difference between bid price and ask price of bonds at issuance.	Bloomberg
MATURITY	Length of maturity of bonds in months.	Bloomberg
AMOUNT_ISSUED	Natural logarithms of issued amounts of bonds.	Bloomberg
GDP	Annual growth rate of real gross domestic growth.	APRA
IMR	Inverse Mills Ratio generated by a Probit model controls for selection bias.	

2.6.1.1 Dependent variables: bank funding costs

Figure 2.2 describes the ADIs' average funding costs, funding premiums and rate sensitive funding costs over time. The WGS period is highlighted by the grey shaded area.

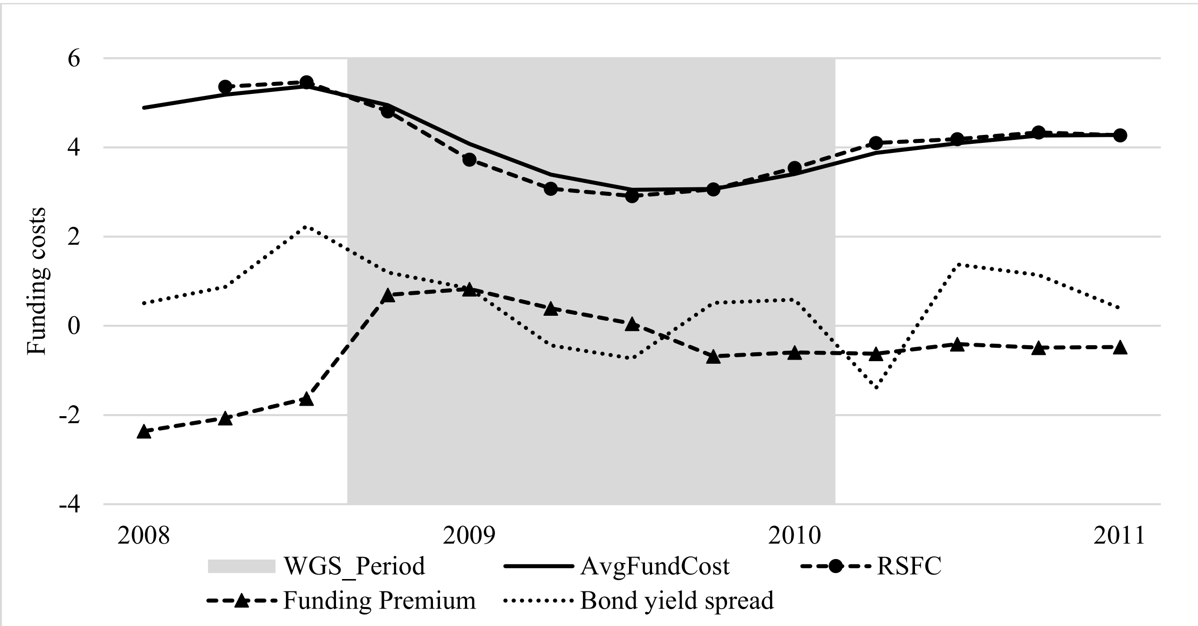

Figure 2.2. Bank funding costs over time

This figure shows average funding costs (AvgFundCost), rate sensitive funding costs (RSFC), funding premiums (FundPremium) and bond yield spreads (Yieldspread) over time. The grey bar indicates the WGS period from November 2008 to March 2010.

The funding costs are also affected by changes in monetary policy (interest rate levels set monthly by the Reserve Bank of Australia) which is why we explicitly control for the cash rate prevailing in the economy in the computation of funding premiums. Bank funding premiums (funding costs less the cash rate) were fairly stable but started to decline from 2006 in the lead up to the GFC as the market's risk appetite increased.

There is a significant run-up in the funding costs faced by ADIs following the GFC. The implementation of the WGS may have helped ADIs to significantly reduce their funding costs. It should be noted that whilst the WGS was in place, ADI funding costs on average even reverted to their 2002 levels. With the help of quantitative easing around the world, ADIs' funding costs have reached new lows, while the funding premiums continued to rise. Whilst the rate sensitive funding costs are of a leading nature they are similar to the average funding costs and both indicate that there is a reliance on a low average maturity of wholesale debt funding in Australia as the difference between the two funding cost measures is rather small.

2.6.1.2 Bank funding costs by WGS participation

Figure 2.3 describes ADIs' funding costs by participation in the WGS. It can be seen that banks that participated in the WGS have on average higher funding costs than non-participants.

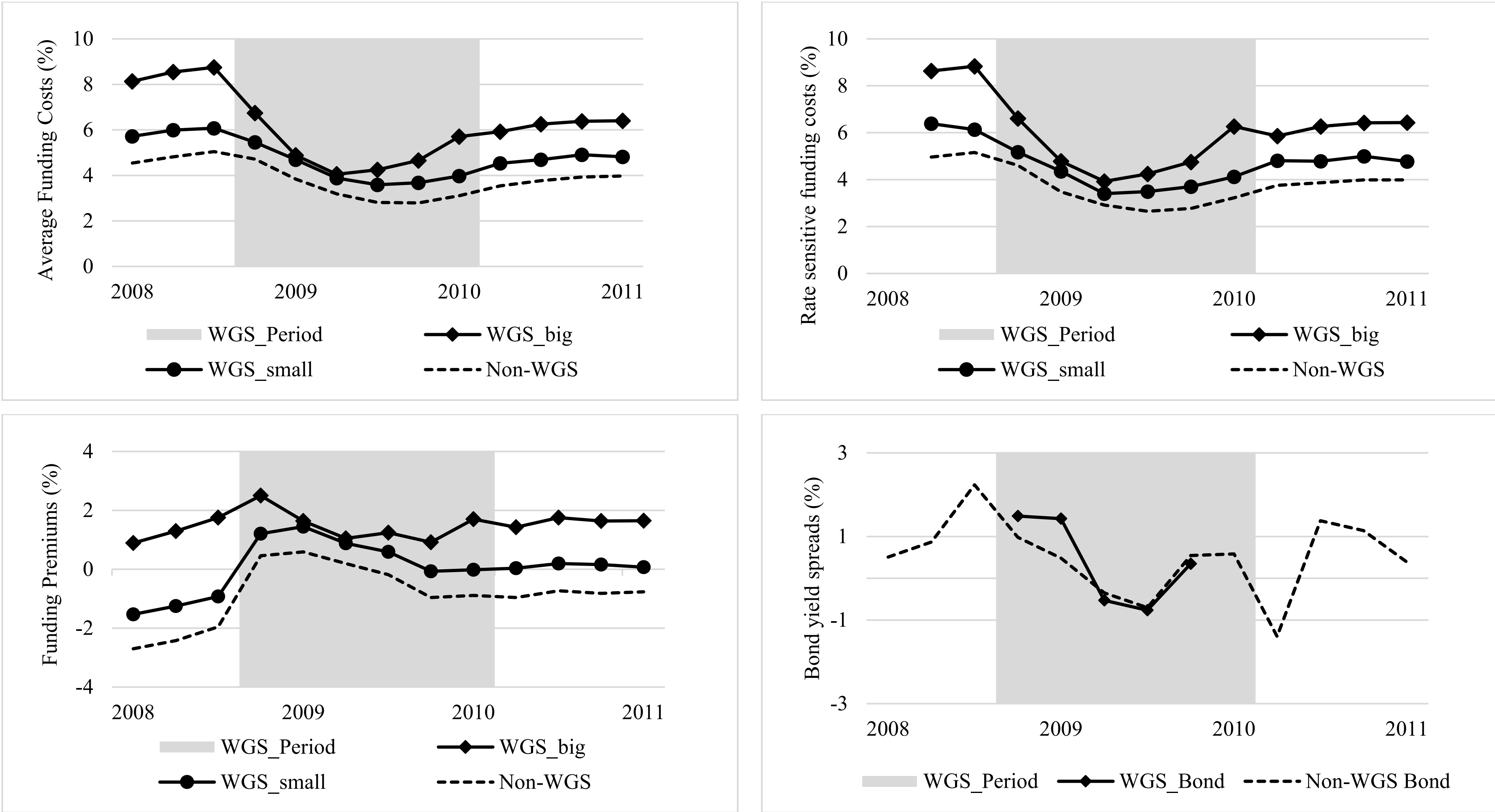

Figure 2.3. Bank funding costs by participation

This figure shows average funding costs, rate sensitive funding costs, funding premiums and bond yield spreads by WGS participation. WGS_Big and WGS_Small are big and small banks that participated in the WGS. Non-WGS represents banks that did not participate in the WGS.

Whilst the funding costs for ADIs that took up the WGS and those that did not moved closely together throughout the whole sample period, the difference in their funding costs were visually reduced whilst the WGS was in place, indicating that the WGS provided ADIs with a significant competitive advantage relative to those that did not take up the WGS. Although the gap in funding costs expanded briefly after the removal of the WGS, it has subsequently narrowed with the monetary easing implemented around the world. Even though existing guarantees remained in place until maturity after the WGS was removed, the funding cost advantage was substantially reduced. The difference in funding costs between participating and non-participating banks supports the necessity to control for the selection of WGS participating banks.

Table 2.2 displays descriptive summary statistics for the non-guarantee and guarantee periods of all ADIs. The funding premium in the non-guarantee was negative for all ADIs, suggesting that average funding costs during that period were lower than the cash rate as deposit rates are often below the risk free rate and offshore wholesale funding is more competitively priced. The funding costs for mutuals are relatively lower than for the pooled sample and for the pooled sample excluding major banks, which is reasonable because the funding structure for mutuals comprises approximately 95% deposits and 5% wholesale liabilities, while for Australian banks, the funding mix normally comprises 65% deposits and 35% wholesale liabilities. We control for these variations in funding structure by including the wholesale liabilities ratio (WLR) in all models.

Table 2.2 Summary statistics of variables by periods

This table shows mean and standard deviation of variables for the non-guarantee and guarantee periods for all ADIs.

	Non-guarantee period		Guarantee period	
AVGFUNDCOST (%)	4.63	(1.36)	3.67	(1.24)
RSFC (%)	4.71	(1.46)	3.54	(1.32)
FUNDING PREMIUM (%)	-1.37	(1.48)	0.13	(1.19)
LEVERAGE (%)	89.13	(5.43)	89.52	(5.20)
Z-SCORE	5.09	(5.04)	3.26	(3.35)
WRITE-OFF (%)	6.76	(98.38)	4.56	(52.34)
RWA_LOAN (%)	77.50	(159.27)	76.93	(134.71)
RWA (%)	46.67	(9.11)	45.70	(8.49)
HOUSINGGR(%)	3.19	(0.14)	3.11	(0.14)
NONHOUSINGGR(%)	1.52	(0.35)	0.76	(0.31)
TOTALLOANGR (%)	2.05	(0.04)	1.84	(0.05)
WGS (%)	26.07	(43.93)	27.58	(44.72)
WGS_SMALL (%)	23.29	(42.29)	24.70	(43.15)
WGS_BIG (%)	2.78	(16.45)	2.88	(16.73)
DURING_GAR (%)	0.00	(0.00)	100.00	(0.00)
REMOVALGAR (%)	45.08	(49.79)	0.00	(0.00)
FCS (%)	45.08	(49.79)	100.00	(0.00)
CAR (%)	18.91	(8.13)	18.68	(7.67)
LAR (%)	4.72	(5.83)	4.89	(6.09)
LLR (%)	0.13	(0.22)	0.14	(0.23)
WLR (%)	8.00	(11.64)	7.65	(11.84)
SIZE	19.31	(233.99)	19.41	(236.02)
FEE_APPLIED (BPS)	145.20	(17.58)	144.78	(18.30)
GDP (%)	0.73	(0.00)	0.40	(0.01)
Obs	864		834	

Table 2.3 provides the summary statistics of large and small ADIs in non-guarantee and guarantee periods. Guaranteed big banks experienced a larger reduction in average funding costs than guaranteed small banks.

Table 2.3 Summary statistics of variables by big and small guaranteed banks

This table shows mean and standard deviation of variables for big and small guaranteed ADIs in non-guarantee and guarantee periods

	Big banks				Small banks			
	Non-guarantee period		Guarantee period		Non-guarantee period		Guarantee period	
AVGFUNDCOST (%)	7.39	(1.43)	5.25	(1.14)	5.40	(1.23)	4.28	(1.18)
RSFC (%)	7.26	(1.53)	5.26	(1.32)	5.49	(1.51)	4.16	(1.47)
FUNDINGPREMIUM (%)	1.52	(0.94)	1.71	(0.85)	-0.50	(1.29)	0.75	(1.10)
LEVERAGE (%)	73.63	(2.80)	74.37	(2.83)	90.07	(5.60)	90.51	(5.64)
Z-SCORE	3.67	(1.58)	2.50	(2.22)	6.41	(6.08)	4.52	(5.16)
WRITE-OFF (%)	0.32	(0.88)	0.18	(0.38)	3.18	(10.02)	2.21	(4.39)
RWA_LOAN (%)	82.97	(20.13)	86.65	(14.13)	69.88	(44.99)	67.72	(39.94)
RWA (%)	56.36	(12.45)	56.57	(9.12)	48.30	(10.47)	47.56	(9.98)
HOUSINGGR(%)	2.53	(0.03)	5.33	(0.09)	3.97	(0.16)	6.02	(0.21)
NONHOUSINGGR (%)	3.08	(0.08)	-0.01	(0.06)	2.56	(0.44)	1.02	(0.39)
TOTALLOANGR (%)	2.80	(0.02)	3.27	(0.06)	2.96	(0.06)	3.47	(0.07)
WGS (%)	100.00	(0.00)	100.00	(0.00)	100.00	(0.00)	100.00	(0.00)
WGS_SMALL (%)	0.00	(0.00)	0.00	(0.00)	100.00	(0.00)	100.00	(0.00)
WGS_BIG (%)	100.00	(0.00)	100.00	(0.00)	0.00	(0.00)	0.00	(0.00)
DURING_GAR (%)	0.00	(0.00)	100.00	(0.00)	0.00	(0.00)	100.00	(0.00)
REMOVALGAR (%)	50.00	(51.08)	0.00	(0.00)	49.25	(50.12)	0.00	(0.00)
FCS (%)	50.00	(51.08)	100.00	(0.00)	49.25	(50.12)	100.00	(0.00)
CAR (%)	11.62	(0.69)	12.54	(1.08)	15.09	(3.22)	14.79	(3.34)
LAR (%)	2.70	(1.05)	2.25	(1.03)	3.69	(4.34)	3.73	(4.06)
LLR (%)	0.35	(0.21)	0.55	(0.22)	0.12	(0.23)	0.18	(0.32)
WLR (%)	37.45	(2.39)	39.05	(2.49)	14.24	(17.57)	14.52	(17.64)
SIZE	26.69	(19.80)	26.72	(14.20)	21.18	(193.54)	21.29	(199.16)
FEE_APPLIED (BPS)	70.00	(0.00)	70.00	(0.00)	138.96	(23.25)	138.20	(24.12)
GDP (%)	0.73	(0.00)	0.40	(0.01)	0.73	(0.00)	0.41	(0.01)
Obs	24		24		201		206	

2.6.1.3 Control variables: bank characteristics and macroeconomic variables

Following the existing literature on bank funding costs, we include several accounting ratios as our independent variables to account for institutional (bank specific) risk. We control for the capital adequacy ratio (CAR) which is the amount of eligible Tier 1 and Tier 2 capital relative to total assets. We expect that the capital adequacy ratio would be negatively related to the banks' funding costs as a strong capital base signals a lower level of default risk. In addition, we also control for liquidity risk and credit risk by using the liquid assets ratio (LAR) which is a ratio of cash and liquid assets relative to total assets and annualised loan loss provisions (LLP) measured as the provisions for bad and doubtful debts divided by total assets. We include the wholesale liabilities ratio (WLR) for wholesale funding relative to total liabilities as a control variable to account for differences in institutional size and funding structures. Large institutions, such as the major banks, may have access to different sources of wholesale funds, and consequently, exhibit systematically different patterns in their funding costs. We also include the size of ADIs as the natural logarithm of total assets. Larger banks are perceived to be less risky due to their greater diversification in asset holdings and funding sources. Furthermore, larger institutions are deemed to be Too-Big-To-Fail, because these large institutions impose significant negative externalities if they are to fail and are more likely to be rescued if faced with financial difficulties (Flannery and Sorescu, 1996; Park and Peristiani, 1998; and Yan et al., 2014). Zelenyuk, Faff and Pathan (2017) analyse the negative impact of size and Basel II disclosure on bank lending growth. In the context of our research, we do not include a dummy variable for too-big-to-fail (TBTF) banks because of multicollinearity between the participation indicator (WGS) and a TBTF indicator as all four Australian major banks participated in the guarantee scheme. Furthermore we do not control for the RWA ratio as it is highly correlated with CAR, and we do not control for bank profitability (with proxies like ROA) as it is related to the dependent variable, *FundingCost*.[7]

In terms of macroeconomic factors, we use the real gross domestic product growth rate (GDP) to proxy for economic conditions. We choose not to include interest rates in our regressions as funding costs as measured by funding premiums, are already computed based on the cash rate. An inclusion of interest rates in the models for average funding costs and rate sensitive funding costs renders comparable models and results are available on request.

[7] However, the results are comparable when we include these terms. Results are available on request.

2.6.2 Regression results

Our results are divided into three parts. Firstly, we examine the effect of WGS participation on alternative measures of funding costs – interest expenses, funding premiums, and rate sensitive funding costs. Secondly, we investigate the impact of the WGS removal. Finally, we study the link between the WGS and bank risk-taking behaviour.

2.6.2.1 The effect of the adoption of WGS

Table 2.4 shows the parameter estimates of the selection model from Equation (1).

Table 2.4 Selection model for bank-level WGS participation

This table shows the selection model for bank-level WGS participation based on significant bank characteristics, including potential fee applied of the guarantee scheme (FEE_APPLIED), bank size (SIZE), wholesale liabilities ratio (WLR), leverage ratio (LEVERAGE), risk weighted assets ratio (RWA) and liquidity ratio (LAR).

	Probability of participation
FEE_APPLIED	-0.1038
	(3.9885)
SIZE	0.5695***
	(0.0716)
WLR	-1.8803
	(1.3598)
LEVERAGE	0.9142
	(2.6091)
RWA	3.0872***
	(1.1149)
LAR	3.3166*
	(1.7115)
Intercept	1.3829
	(598.30)
Obs	474
R-square	54.49%

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

We find that large banks, banks with larger size, greater risk-weighted assets ratio (RWA) and higher liquidity (LAR) were more likely to participate in the WGS. WLR is insignificant and we hypothesise that this is due to the positive correlation with size (65%) as large banks are reliant on wholesale liabilities than small banks.[8] Note all correlations are substantially smaller.

In Table 2.5, column (1), (2) and (3) report the effect of the WGS on ADI funding costs according to Equation (3) and controlling for the Inverse Mills Ratio (IMR) from Equation (2). The *DURINGGAR* coefficients indicate that the average funding costs, and rate sensitive funding costs reduced after the WGS, as the parameter estimate is negative and significant while the WGS estimate is positive and significant indicating that the funding costs were generally higher for banks that participated in the WGS. The negative and significant estimate of our DiD estimators, *WGS_SMALL* DURINGGAR and WGS_BIG*DURINGGAR* suggests that banks that took up the guarantee scheme, had lower funding costs relative to banks that did not. Specifically, during the guarantee period, average funding costs reduced by 121 bps for big banks and 33 bps for small banks that voluntarily adopted the WGS.

Consistent with our expectations, larger ADIs that chose to participate in the WGS experienced a more economically significant reduction in funding costs than the smaller ones and also the mutuals.

[8] We also omitted WLR in the stage I regression and obtained comparable results that are available on request.

Table 2.5 Impact of WGS participation and removal on funding costs

*The difference-in-differences (DiD) estimates of WGS_BIG*DURINGGAR and WGS_SMALL*DURINGGAR show the adoption impact of the WGS on funding costs and the DiD estimates of WGS_BIG*REMOVALGAR and WGS_SMALL*REMOVALGAR show the removal impact of the WGS on funding costs of big and small banks respectively.*

	Adoption effect			Removal effect		
	Average funding cost	Rate sensitive funding cost	Funding premium	Average funding cost	Rate sensitive funding cost	Funding premium
	(1)	(2)	(3)	(4)	(5)	(6)
WGS_BIG* REMOVALGAR				**-0.0135*** **	**-0.0144*** **	**-0.0138** **
				(0.0049)	(0.0036)	(0.0054)
WGS_SMALL* REMOVALGAR				**-0.0022* **	**-0.0034* **	**-0.0020* **
				(0.0012)	(0.0020)	(0.0012)
REMOVALGAR				-0.0111***	-0.0110***	0.0149***
				(0.0008)	(0.0010)	(0.0009)
WGS_BIG* DURINGGAR	**-0.0121*** **	**-0.0091*** **	**-0.0118*** **	-0.0187***	-0.0176***	-0.0186***
	(0.0019)	(0.0026)	(0.0019)	(0.0040)	(0.0044)	(0.0042)
WGS_SMALL* DURINGGAR	**-0.0033*** **	**-0.0038** **	**-0.0033*** **	-0.0044***	-0.0058**	-0.0043***
	(0.0010)	(0.0015)	(0.0009)	(0.0013)	(0.0025)	(0.0013)
WGS_BIG	0.0100	-0.0193	0.0393	0.0095	-0.0214	0.0393
	(0.0385)	(0.0568)	(0.0440)	(0.0380)	(0.0540)	(0.0433)
WGS_SMALL	0.0048	-0.0124	0.0274	0.0008	-0.0182	0.0237
	(0.0285)	(0.0443)	(0.0329)	(0.0280)	(0.0424)	(0.0323)
DURINGGAR	-0.0040***	-0.0066***	0.0072***	-0.0155***	-0.0180***	0.0216***
	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0009)	(0.0007)
FCS	-0.0118***	-0.0119***	0.0142***			
	(0.0010)	(0.0008)	(0.0011)			
CAR	-0.0832***	-0.0951***	-0.0937***	-0.0853***	-0.0963***	-0.0959***
	(0.0214)	(0.0328)	(0.0223)	(0.0214)	(0.0326)	(0.0224)
LAR	0.0266***	0.0201**	0.0179*	0.0248***	0.0186*	0.0160*
	(0.0088)	(0.0102)	(0.0092)	(0.0086)	(0.0102)	(0.0091)
LLR	-0.0773	0.2494	-0.0643	-0.0931	0.2396	-0.0818
	(0.0992)	(0.3542)	(0.0972)	(0.1005)	(0.3531)	(0.0970)
WLR	0.0081	0.0168	-0.0007	0.0067	0.0157	-0.0021
	(0.0109)	(0.0140)	(0.0111)	(0.0106)	(0.0138)	(0.0108)
LEVERAGE	-0.0304	-0.0793	-0.0051	-0.0303	-0.0774	-0.0053
	(0.0370)	(0.0677)	(0.0404)	(0.0350)	(0.0675)	(0.0377)
RWA	-0.0328*	-0.0337*	-0.0401**	-0.0361**	-0.0365**	-0.0436**
	(0.0181)	(0.0176)	(0.0197)	(0.0165)	(0.0171)	(0.0181)
Z-SCORE	0.0001	0.0001**	0.0000	0.0001*	0.0001**	0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0)	(0.0001)	(0.0001)
SIZE	0.0020	0.0040	0.0000	0.0028	0.0052	0.0008
	(0.0036)	(0.0050)	(0.0001)	(0.0035)	(0.0046)	(0.0040)
GDP	-0.5654***	-0.6313***	-0.2126***	-0.5674***	-0.6353***	-0.2147***
	(0.0242)	(0.0450)	(0.0238)	(0.0244)	(0.0455)	(0.0239)
Intercept	0.0676	0.0737	0.0054	0.0553	0.0506	-0.0054
	(0.0579)	(0.0867)	(0.0678)	(0.0554)	(0.0824)	(0.0650)
IMR	-0.0039	0.0073	0.0025	-0.0041	0.0084	0.0021
	(0.0186)	(0.0187)	(0.0203)	(0.0177)	(0.0192)	(0.0194)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1698	1530	1698	1698	1530	1698
R-square	81.55%	74.55%	84.75%	81.89%	74.88%	85.04%

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

We further explore the influence of bank size on the sensitivity of our funding cost measures to WGS by introducing triple difference-in-differences estimators. *WGS_BIG*DURINGGAR*WLR* and *WGS_SMALL*DURINGGAR*WLR* are whether the reduction in funding costs for guaranteed banks is sensitive to the wholesale debt funding WLR (as the capacity to borrow based on their credit ratings and credit spreads).

The results are in Table 2.6. The estimates of *WGS_BIG*DURINGGAR*WLR* are negative and significant, suggesting that the impact of the WGS on large banks' funding costs are highly sensitive to the wholesale liabilities ratio. The estimates of *WGS_SMALL*DURINGGAR*WLR* are insignificant, showing the weak sensitivity of the WGS to the wholesale liabilities ratio of small banks. Overall, the finding of greater funding cost reduction for big banks relative to small banks may be attributed to the too-big-to-fail perceptions.

Table 2.6 Sensitivity of the WGS to wholesale funding

*The triple DiD estimates of WGS_BIG*DURINGGAR*WLR and WGS_SMALL*DURINGGAR*WLR show how sensitive the wholesale liabilities ratio affect a reduction of funding costs for guaranteed big and small banks respectively.*

	Average funding cost	Rate sensitive funding cost	Funding premium
WGS_BIG*DURINGGAR *WLR	**-0.1124****	**-0.3075*****	**-0.0815*****
	(0.0481)	(0.0706)	(0.0202)
WGS_SMALL*DURINGGAR *WLR	**-0.0121**	**-0.0021**	**-0.0037**
	(0.0108)	(0.0110)	(0.0089)
WGS_BIG*WLR	-0.1124**	-0.3075***	-0.0815***
	(0.0481)	(0.0706)	(0.0202)
WGS_SMALL*WLR	0.0170	0.0187	0.0176
	(0.0181)	(0.0266)	(0.0174)
DURINGGAR*WLR	0.0012	-0.0003	-0.0079
	(0.0078)	(0.0081)	(0.0057)
WGS_BIG*DURINGGAR	0.0307	0.1085***	0.0217**
	(0.0199)	(0.0290)	(0.0097)
WGS_SMALL*DURINGGAR	-0.0121	-0.0021	-0.0037
	(0.0108)	(0.0110)	(0.0089)
WGS_BIG	-0.0093	-0.0746	0.0123
	(0.0407)	(0.0553)	(0.0510)
WGS_SMALL	0.0011	-0.0167	0.0243
	(0.0291)	(0.0420)	(0.0335)
DURINGGAR	-0.0041***	-0.0066***	0.0074***
	(0.0006)	(0.0006)	(0.0006)
FCS	-0.0118***	-0.0119***	0.0143***
	(0.0010)	(0.0008)	(0.0011)
CAR	-0.0858***	-0.0958***	-0.0962***
	(0.0225)	(0.0322)	(0.0239)
LAR	0.0267***	0.0195*	0.0177*
	(0.0088)	(0.0101)	(0.0094)
LLR	-0.0509	0.2561	-0.0377
	(0.0976)	(0.3546)	(0.0964)
WLR	0.0001	0.0052	-0.0086
	(0.0111)	(0.0115)	(0.0098)
Leverage	-0.0375	-0.0841	-0.0130
	(0.0424)	(0.0680)	(0.0469)
RWA	-0.0329*	-0.0341*	-0.0401*
	(0.0192)	(0.0174)	(0.0210)
Z-score	0.0001	0.0001**	0.0
	(0.0111)	(0.0001)	(0.0001)
Size	0.0023	0.0043	0.0003
	(0.0035)	(0.0047)	(0.0041)
GDP	-0.5659***	-0.6311***	-0.2147***
	(0.0227)	(0.0443)	(0.0226)
Intercept	-0.0008	0.0089	0.0062
	(0.0186)	(0.020)	(0.0723)
IMR	0.0672	0.0718	0.0062
	(0.0622)	(0.0855)	(0.0723)
Bank fixed effects	Yes	Yes	Yes
Obs	1698	1530	1698
R-square	81.69%	74.73%	84.89%

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

2.6.2.2 The effect of the removal of WGS

In Table 2.5, column (4), (5) and (6) show the estimates for Equation (4). We include the variable *REMOVALGAR* that takes the value of one for the periods after the removal of the guarantee and the value of zero for the periods before and during the guarantee.

The result on the impact of the removal of the guarantee scheme is shown in column (4), (5) and (6) in Table 5. It can be observed for all funding cost measures and data sub-segments that the estimates of the DiD estimator, *WGS_SMALL*REMOVALGAR*, are negative and significant at 10% level. This indicates that unlike the decision to participate, the removal of the guarantee had little significant impact on small ADIs' funding costs and funding premiums. This can be attributed to the fact that a large amount of wholesale funds remained insured until maturity (i.e., up to another five years) after the removal of the guarantee.

Moreover, the market potentially believed that an implicit government guarantee extended beyond the removal of the WGS. Hence, we find that the coefficient estimate for *WGS_BIG*REMOVALGAR* is consistently negative and significant, meaning that the big four banks continued to benefit from a funding cost reduction beyond the official removal of the WGS. Specifically, after the WGS was closed, average funding costs continued to be reduced by 135 bps for big banks and 22 bps for small banks. This suggests that the four major banks in Australia continued to benefit from an implicit guarantee after the explicit guarantee was removed corroborating with Acharya et al.'s (2016) observations regarding banks that are too-big-to-fail. Our results also shed new light on the recent findings of Boyle et al. (2015) in that we do not find depositors or debt investors are more sensitive and quicker to withdraw their funds from ADIs when insurance gets provided for the first time during a financial crisis in banks that are deemed to be too-big-to-fail.

2.6.2.3 Bank Risk-taking

In column (1), (2) and (3) of Table 2.7 we report the parameter estimates for Equation (5). We analyse alternative proxies for bank risk-taking: (i) banks' Z-scores, (ii) write-off ratio, (iii) and risk-weighted assets to net loan ratio (*RWA_LOAN*).

The regressions for the Z-scores, loan write-off ratio and risk-weighted assets to net loan ratio show insignificant coefficients for *WGS_BIG*DURINGGAR* and *WGS_SMALL*DURINGGAR,* indicating that the WGS did not lead to excessive risk-taking for guaranteed banks. The sign of *WGS_BIG*DURINGGAR* and *WGS_SMALL*DURINGGAR* are positive for Z-scores and negative for the loan write-off ratio and risk-weighted assets to net loan ratio indicating that bank risk appears to be lower for guaranteed banks post implementation.

Overall, our bank risk-taking tests indicate that the WGS did not fuel bank risk taking during the height of the 2008 GFC period consistent with recent cross-country findings by Anginer et al. (2014). One explanation for this emanates from the prior work of Bollen et al. (2015), who argue that during the peak of the GFC, Australian banks were seeking to ensure their survival rather than to take more risk. Hence, we also do not find a systematic increase in bank risk fuelled by the government guarantee. In the following, we find evidence that Australian banks also used the cheaper funding to support credit growth in the Australian housing sector following their adoption of the WGS.

Table 2.7 Impact of WGS participation on bank risk-taking and loan growth rates

*The DiD estimates of WGS_BIG*DURINGGAR and WGS_SMALL*DURINGGAR show the impact of the WGS on risk-taking proxies and loan growth rates of big and small banks respectively.*

	Risk taking effect			Loan growth effect		
	Z-score	Write-off	RWA_Loan	Housing loan growth	Non-housing loan growth	Total loan growth
	(1)	(2)	(3)	(4)	(5)	(6)
WGS_BIG* DURINGGAR	**0.7842**	**-0.2336**	**-0.1282**	**0.0433***	**-0.0654***	**0.0059**
	(0.7341)	(0.1949)	(0.1847)	(0.0220)	(0.0345)	(0.0126)
WGS_SMALL* DURINGGAR	**0.1740**	**-0.0051**	**-0.0682**	**0.0294**	**-0.0137**	**0.0093**
	(0.6741)	(0.0264)	(0.0488)	(0.0233)	(0.0556)	(0.0077)
WGS_BIG	-14.5078	3.2285	1.0811	-0.8668	-0.6002	-0.4979*
	(9.2222)	(2.1668)	(2.0588)	(0.5585)	(1.0120)	(0.2789)
WGS_SMALL	-12.8517*	1.8559	0.3386	-0.6000	-0.7329	-0.4303**
	(7.5994)	(1.1978)	(2.1348)	(0.4377)	(0.8049)	(0.2173)
DURINGGAR	-1.5250***	-0.0965	-0.0260	-0.0001	-0.0070	0.0019
	(0.2882)	(0.0823)	(0.0202)	(0.0071)	(0.0360)	(0.0040)
FCS	-0.9980**	0.1815	0.0693*	-0.0307***	0.0163	-0.0193***
	(0.4458)	(0.1619)	(0.0396)	(0.0111)	(0.0343)	(0.0064)
CAR	7.4813	5.5998	-2.1258***	-0.4006	0.6552	-0.1025
	(7.9283)	(4.7000)	(0.5606)	(0.3730)	(1.0744)	(0.1377)
LAR	0.5499	-2.3853	0.0992	0.0352	-0.5704	-0.2303***
	(3.2795)	(2.1971)	(0.6575)	(0.1028)	(0.4634)	(0.0704)
LLR	-73.0412	85.4127	85.5620	-1.5328	5.5986*	0.1556
	(47.6927)	(68.2572)	(82.0616)	(1.3138)	(2.9465)	(1.6594)
WLR	3.7084	0.9845	0.2804	0.3266*	0.4816	0.1643***
	-3.357	(0.9485)	(0.5274)	(0.1962)	(0.6035)	(0.0458)
Leverage				-0.4991*	-0.1994	-0.0978
				(0.2778)	(0.7537)	(0.1585)
RWA				-0.1427	0.7558*	0.0572
				(0.1739)	(0.4007)	(0.0843)
Z-score				-0.0016*	-0.0018	-0.0006**
				(0.0009)	(0.0029)	(0.0003)
Size	1.9731**	-0.5182	-0.1550	0.0837	-0.0189	0.0381
	(0.9369)	(0.3974)	(0.1822)	(0.0542)	(0.0938)	(0.0276)
GDP	-9.8769	0.4160	0.1415	-0.5026	-1.1889	-0.7059***
	(12.0232)	(1.1203)	(0.8120)	(0.9276)	(2.0709)	(0.2531)
Intercept	-38.4788**	10.1733	3.7961	-0.9878	1.0257	-0.3961
	(16.9208)	(8.4477)	(3.1645)	(0.8942)	(1.6933)	(0.4552)
IMR	9.2304	-2.8479	-0.4048	0.2023	-1.2848*	-0.2166**
	(5.8408)	(3.3036)	(0.3894)	(0.2248)	(0.6506)	(0.1087)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1698	1698	1698	1698	1698	1698
R-square	49.95%	27.36%	74.52%	9.19%	11.09%	32.64%

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

2.6.2.4 Relationship between the WGS and loan growth

In this section, we explore the observed increases in absolute lending may have fuelled increases in debt funded bank lending across the banking sector. The results in column (4), (5) and (6) of Table 2.7 show the parameter estimates for Equation (6) and report impact of the WGS on the growth of housing loans, non-housing loans, and total loans.

The DiD estimators, *WGS_SMALL*DURINGGAR* are insignificant for all loan growth measures, indicating that for small banks, the WGS did not have an effect. However, the DiD estimator *WGS_BIG*DURINGGAR* is positive and significant for explaining housing loan growth. The growth is also economically significant as large banks' loan books grew by 4.3 percent during the WGS period. This empirical evidence indicates that large banks were able to increase credit supply in the housing sector funded by the access to cheaper wholesale debt.

Our findings suggest that large banks picked up the slack left by a reduction in small banks shares in housing loan markets as documented by Bollen et al. (2015). This also suggests that the WGS unintentionally increased indebtedness in both banks and household sectors. However, for non-housing loan growth regression, the DiD estimator *WGS_BIG*DURINGGAR* is negative and significant with an estimate of -2.9 percent, indicating that banks' loan portfolio witnessed a shift from non-housing loans to housing sector.

2.6.3 Robustness check

2.6.3.1 Propensity score matching with bootstrapping

We ease the concern regarding the selection issue by creating a propensity score matched sample of ADIs, as the participation in the WGS was not random. To confirm the results, we construct a propensity score matched sample using the Inverse Mills Ratio (IMR) from our Stage 1 model estimated with ex-ante bank characteristics and draw subsamples randomly stratified to ensure an equal number of WGS participating and non-participating banks for a given IMR group and hence probability to participate. We find a match of 23 treated banks and 23 control banks, yielding 520 observations in the subsample. This is the sum of the minimum number of matched banks over the five IMR groups.

Table 2.8 shows the mean summary statistics of the ex-ante characteristics of guaranteed and non-guaranteed ADIs and average p-values of a test for equality of means over 100 bootstrap iterations.

Table 2.8 Robustness check: ex-ante characteristics on propensity score matching

This table shows summary statistics of ex-ante characteristics of guaranteed and non-guaranteed ADIs based on propensity score matching of 100 simulated subsamples. The p-value is received from t-tests and averaged over 100 simulated subsamples.

	WGS=1	WGS=0	Avg. p-value
IMR	0.5417	0.5810	0.2091
Fee_applied (bps)	142.1957	150.0000	0.1255
Size	20.5377	19.9058	0.2761
WLR (%)	9.9496	6.1043	0.2925
Leverage (%)	89.6397	90.9187	0.3688
RWA (%)	48.1810	46.5429	0.4779
LAR (%)	3.2948	3.4722	0.6029
CAR (%)	15.3131	17.0946	0.1397
LLR (%)	0.0967	0.0785	0.6271
No. of banks	23	23	

Table 2.9 shows the statistics of a bootstrap with 100 random subsamples and reports the average treatment effect of both the adoption and removal of the government guarantee, *WGS*DURINGGAR* and *WGS*REMOVALGAR*. As we have matched propensity scores for subsamples, we no longer distinguish the treatment effect for big and small banks. Instead, in the following regression tests, we use a dummy variable, WGS, that takes the value of 1 if banks took up the scheme and 0 otherwise. Thus, the treatment effect is measured through the

difference-in-differences estimators *WGS*DURINGGAR* and *WGS*REMOVALGAR*. All results are consistent with the main tests.

Table 2.9 Robustness check: results on bootstrapping test

*This table shows the statistics of a bootstrap with 100 random subsamples and reports the average treatment effect of both the adoption and removal of the government guarantee. The parameter estimate of WGS*DURINGGAR and WGS*REMOVALGAR in regression models for tests of adoption effect, removal effect, risk-taking effect and loan growth effect.*

	Mean	SD	P5	P50	P95	Avg. p-value
Panel A: Adoption effect			WGS*DURINGGAR			
AvgFundCost	-0.0022	0.0006	-0.0032	-0.0022	-0.0012	0.1183
RSFC	-0.0025	0.0010	-0.0044	-0.0022	-0.0013	0.1091
FundingPremium	-0.0023	0.0006	-0.0033	-0.0022	-0.0013	0.1510
Panel B: Removal effect			WGS*REMOVALGAR			
AvgFundCost	-0.0010	0.0009	-0.0024	-0.0010	0.0006	0.4821
RSFC	-0.0018	0.0014	-0.0043	-0.0019	0.0004	0.3950
FundingPremium	-0.0010	0.0010	-0.0025	-0.0011	0.0008	0.4695
Panel C: Risk-taking effect			WGS*DURINGGAR			
Z-score	0.5120	0.4706	-0.2281	0.5101	1.2375	0.5914
Write-off ratio	-0.0065	0.0036	-0.0119	-0.0062	0.0002	0.5115
RWA_Loan	-0.0159	0.0057	-0.0247	-0.0156	-0.0073	0.3689
Panel D: Loan growth effect			WGS*DURINGGAR			
Housing loan	0.0340	0.0096	0.0201	0.0324	0.0505	0.2258
Non-housing loan	-0.0056	0.0362	-0.0717	-0.0027	0.0539	0.6352
Total loan	0.3226	0.1912	0.0826	0.2804	0.6899	0.3226

Panel A of Table 2.9 shows the adoption effect of the WGS on the alternative funding cost proxies. The mean of the estimates of *WGS*DURINGGAR* on 100 random subsamples is negative, suggesting a consistent reduction in funding costs from adopting the government guarantee on bank liabilities.

Panel B of Table 2.9 shows the removal effect of the WGS on funding cost proxies. The mean of the estimates of *WGS*REMOVALGAR* on 100 random subsamples is negative, suggesting that guaranteed ADIs continued to benefit from a reduction in funding cost beyond the official guarantee period.

Panel C of Table 2.9 shows the stabilising effect of the WGS on alternative risk proxies. The positive mean of the estimates of *WGS*DURINGGAR* on Z-scores, and the negative mean of estimates of *WGS*DURINGGAR* on the loan write-off ratio and risk-weighted assets to net loans imply that the WGS did not cause excessive risk taking.

Panel D of Table 2.9 shows the loan growth effect of the WGS on housing loans, non-housing loans and total loans. Again, the positive mean of housing loan growth and negative mean of non-housing growth suggest that guaranteed banks shifted their loan portfolios into housing loans thereby reducing their riskiness.

Taken together, our findings further corroborate the international evidence of Anginer, Demirguc-Kunt and Zhu (2014) on the benefits from a financial stability perspective of introducing explicit protection for depositors in times of financial crises. Explicit protection and government guarantees offered in times of financial crises creates less of a moral hazard problem than that previously documented in normal times (Demirgüç-Kunt and Huizinga, 2004; Ioannidou and Penas, 2010). Whilst they help to restore investor confidence in the banking system and significantly lowers funding costs for banks, rampant risk-taking becomes less of a concern even with an expansion in credit supply.

2.6.3.2 Bond yield spreads

As a second robustness check, we collected the bid and ask yields at origination of all bonds issued by Australian ADIs during our sample period. We excluded covered bonds, bonds with embedded options and conversion features to ensure that our bond sample is comparable. We study 196 bonds issued by six Australian banks from 2008 to 2012 (100 bonds were issued outside of the WGS period and 96 bond issues occurred during the WGS period. During the WGS period, we identify 30 bonds that were guaranteed[9] and 66 bonds that were not guaranteed. We compute the yield spread above the US treasury rate of equal maturity as all bonds were issued in US dollars. Table 2.10 shows the summary statistics for the bond data during the guarantee period and over the full time period. The bond yield spreads during the WGS are significantly lower than the average yield spreads during the full time period. All bond spreads relate to bank issuers with a rating of A3 by Moody's (respectively A- by Standard and Poor's) or better.

Table 2.10 Robustness check: summary statistics of bonds issued by Australian banks

This table shows mean and standard deviation of variables for bonds issued by Australian banks during the observation period and guarantee period.

	Full period from 2008 to 2012		Guarantee period from Nov 2008 to Mar 2010	
	Mean	SD	Mean	SD
YIELDSPREAD	44.43	(121.30)	12.93	(116.63)
WGS_BOND	15.31	(36.10)	31.25	(46.59)
PREGAR	1.02	(10.08)	0.00	(0.00)
DURINGGAR	48.98	(50.12)	100.00	(0.00)
POSTGAR	11.22	(31.65)	0.00	(0.00)
BIDASKSPREAD	10.01	(32.01)	12.61	(43.98)
MATURITY	60.85	(38.43)	52.00	(23.07)
AMOUNT_ISSUED ($M)	943.97	(720.71)	1,281.61	(655.85)
Obs	196		96	

Table 2.11 reports the likelihood of seeking a WGS guarantee for a bond issue based on Equation (7). The model controls for bond features including the bid-ask spread and issuance amount as well as issuer-specific variables such as funding structure (WLR and Leverage) and bank risks (RWA and LAR). It can be seen that banks with a higher wholesale liabilities ratio

[9] The Reserve Bank of Australia provides public information on the list of bond issues and the issuance amounts that were guaranteed by the WGS on their website, www.rba.gov.au

(WLR) have a higher propensity for their bonds to be guaranteed by the WGS. It should be noted that we do not control for the issuer rating because the bond sample only has six Australian banks allocated in two neighbouring categories of credit ratings (Aa and A). From this model we compute the Inverse Mills Ratio (IMR) following Equation (2).

Table 2.11 Robustness check: selection model for bonds guaranteed

This table shows the selection model for bonds taking up the government guarantee scheme.

	Probability of bonds taken up guarantee
BIDASKSPREAD	-0.1514
	(0.3912)
AMOUNT_ISSUED	0.2841***
	(0.1092)
WLR	6.1085***
	(2.1482)
LEVERAGE	-1.5407
	(2.4120)
RWA	-0.4216
	(1.1772)
LAR	-10.7640*
	(6.1107)
Intercept	-7.5660**
	(3.0070)
Obs	196
R-square	0.207

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

Table 2.12 shows the parameter estimates for the second stage model whilst controlling for the Inverse Mills Ratio. We run two regression models for bond yield spreads, the first model considers the standalone effect of the WGS on bond yield spreads and the second one controls for period fixed effects. Model 1 shows that yield spreads for bonds insured by the WGS were significantly lower by an average of 47.5 basis points than bond yield spreads for non-guaranteed bonds. Model 2 shows the same result in that yield spreads for bonds guaranteed by the WGS were significantly lower than yield spreads for non-guaranteed bonds even with period fixed effects. The main benefit of this specification is that it controls for all unobservable characteristics specific to individual bond issues in a given year and helps to mitigate potential omitted variables bias.

Table 2.12 Robustness check: impact of WGS participation on bond yield spreads

This table reports the impact of WGS participation on bond yield spreads. The estimate of WGS_BOND shows the impact of the WGS on bond yield spreads.

	Bond yield spread	
WGS_BOND	**-0.4748*** **	**-0.2702** **
	(0.0686)	(0.0819)
PREGAR		1.6760***
		(0.2106)
DURINGGAR		-0.4900**
		(0.1525)
POSTGAR		0.0031
		(0.3271)
BIDASKSPREAD	0.4527	0.3747
	(0.2646)	(0.2420)
MATURITY	0.0080***	0.0082***
	(0.0010)	(0.0012)
AMOUNT_ISSUED	0.2642	0.4350**
	(0.1860)	(0.1352)
CAR	1.4275	10.7407
	(9.8904)	(5.5165)
LAR	-2.5390	-10.4305
	(8.9174)	(5.5900)
LLR	-44.6401**	-32.3418*
	(11.7204)	(13.5881)
WLR	5.4455	8.2984*
	(4.5409)	(3.6886)
LEVERAGE	3.0580	2.7670
	(1.9254)	(1.7545)
RWA	0.7679	-0.6005
	(1.2450)	(0.5871)
Z-SCORE	0.0077*	0.0095
	(0.0038)	(0.0049)
SIZE	-0.0615	-0.1563
	(0.3650)	(0.2836)
IMR	7.0683	11.7645**
	(6.9000)	(4.2408)
Obs	196	196
R-square	34.78%	38.62%

Note: Standard errors are clustered at the bank level and presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

Model 2 also shows the impact of each single period before, during and after the guarantee scheme with four dummy variables. PREGAR indicates the three quarters prior to the guarantee scheme and shows a positive but insignificant effect on bond yield spreads. During the WGS period, bond yield spreads were significantly reduced, which is supported by a negative and significant coefficient on DURINGGAR. The unambiguous reduction in bond yield spreads for banks that adopted the WGS is consistent with Black et al.'s (2016) finding that government guarantees enhance the liquidity in bank bonds. In the last three quarters after the closure of the guarantee scheme, we find that bond yields did not change materially, which is supported by the negative but insignificant coefficient on POSTGAR. This also confirms our findings on the removal effect of the WGS, suggesting that the WGS removal had no significant effect on bond yield spreads. Furthermore, we are interested in the relative incentive of banks to guarantee bond issues using the WGS. We quantify the relative benefit of banks issuing bonds as part of the WGS.

We reveal in Table 2.12 that wholesale funding costs (expressed in bond yield spreads at issuance) reduced by 27.2 bps with the government guarantee. Moreover, the gross implied reduction in bond yield spreads for guaranteed bonds can be computed as the 27.2 bps standalone reduction of guaranteed bond yield spreads (estimate of *WGS_BOND)* plus the reduction for the period during the WGS (*DURINGGAR*) in Model 2 of Table 12 amounting to a total reduction of 76.02 bps. The average fee paid on guaranteed bonds suggested by mapping bonds covered by the WGS to the fee charged for the guarantee based on the issuer rating and is 70 bps. Hence, the *net* benefit for guaranteed bonds is 6.2 bps (i.e., the difference between the gross implied reduction in yield spreads and the average fee paid). Whilst the net benefit of 6.2 bps is positive the small amount also suggests that not all bonds may benefit from a lower net yield spread which explains why some bonds continued to be issued without the WGS guarantee during the WGS period.

2.7 Conclusions

In this study, we investigate whether the introduction of a government guarantee on bank debt by the Australian government, following the 2007-2009 Global Financial Crisis (GFC), had material impact on the funding costs of banks. Firstly, we empirically examine the impact of WGS participation and guarantee removal on different types of deposit-taking institutions' average funding costs, funding premiums, as well as rate sensitive funding costs. Secondly, we analyse the effect of the removal of the WGS on bank funding costs. Thirdly, we analyse the impact of the WGS on bank risk-taking and lending behaviour.

We find strong empirical evidence that Australian banks entering into the guarantee experienced a significant reduction in their funding costs and funding premiums. In contrast, we showed that the subsequent removal of the guarantee did not result in a full repricing of funding costs back to normal levels. Furthermore, we find a risk-taking decrease in terms of general bank risk, asset risk or liquidity risk. The analysis of loan growth rates confirms that banks allocated the additional debt funding to residential mortgage loans coinciding with a period of strong growth in house prices in Australia.

An analysis of guaranteed and non-guaranteed bonds confirms that the guarantee reduced the funding costs of banks. Our findings support the economic rationale for banks to participate in the WGS given the pricing of the guarantee fees.

Our findings are important for policy makers in two ways: firstly, our results show the efficacy of the WGS. The introduction of the wholesale funding guarantee was effective in helping ADIs to secure wholesale debt funding at reasonable costs during the GFC and as intended it supported consumer confidence by lowering actual and perceived bank risks within the financial system. This we find the WGS led to a significant reduction in bank funding costs. However, we found that the removal of the guarantee scheme had no effect on ADIs' funding costs, which is a unique finding as to our best knowledge, there has been no previous study on the effect of the removal of any wholesale funding guarantee scheme in the world, especially in a setting without any explicit protection on bank deposits or other forms of bank debt. This suggests that the effects of the WGS may continue to persist in the form of an implicit subsidy for an extended period after the closure of the WGS given the precedence with having an explicit government guarantee. Secondly, the adoption of the guarantee may have led to stronger growth in residential mortgage lending. This highlights that sound regulation is required to restrict the moral hazard problem that is associated with a wholesale funding guarantee.

Future research on government guarantees should focus on the ways in which banks can respond more quickly to the removal of explicit government guarantees to ensure that a level playing field can be restored in a manner that is least disruptive on credit supply and ultimately the real economy.

Chapter 3: Prepayment Selection in Mortgage Credit Risk

3.1 Abstract

This paper analyzes the effect of prepayment selection in US prime mortgages on credit risk. 60% of mortgages are prepaid within the first ten years despite substantially longer tenors of thirty years. We document a u-shaped relation between default risk and prepayment risk. Default risk is high for low and high prepayment risk. Default risk is low for medium prepayment risk. We find that two effects explain this relation: an unconditional effect based on observed risk factors explains high default rates for low-prepayment-risk loans and a selection effect based on correlated unobservable factors explains high default rates for high-prepayment-risk loans. The unconditional effect dominates in economic downturns and the selection effect in economic upturns. Current models may underestimate the additional default risk attributed to the selection effect and we propose a two-stage model with a novel correction term to achieve a better accuracy of default predictions.

3.2 Introduction

3.2.1 Motivation

Residential mortgage loans are the dominant asset class on banks' balance sheets. Mortgage terminations include maturities, prepayments and defaults. Most economies give borrowers the right to prepay with low hurdles before the maturity date.

Figure 3.1 shows the cumulative percentages of defaults and prepayments[10] by loan age, which is calculated from our empirical data. The prepayment rate is approximately 10% of loans after the first year and 60% after ten years.

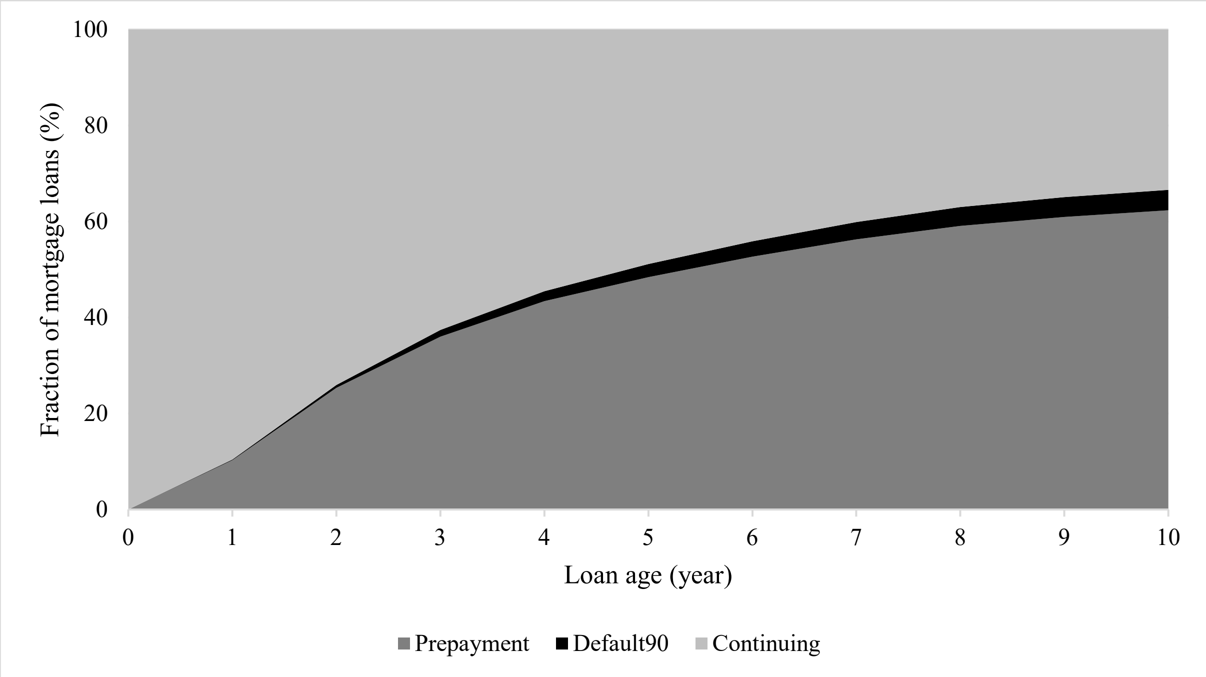

Figure 3.1. Cumulative prepayment and default rates over loan age

This figure shows the cumulative fraction of prepaid and defaulted loans in the first ten years of the loans' lifetime. The sample comprises of nearly 23 million loan accounts originated and observed from 2000 to 2016 by annual basis.

Prepayment is a selection mechanism. Mortgage prepayments imply that a loan exits and a borrower is no longer observed. The subsequent stage of default outcomes is only received on the sample of non-prepaid loans. This selection mechanism is illustrated in Figure 3.2.

[10] Prepayment may be a slow process and in this paper we consider full prepayment after which a mortgage loan exits the loan portfolio of a bank.

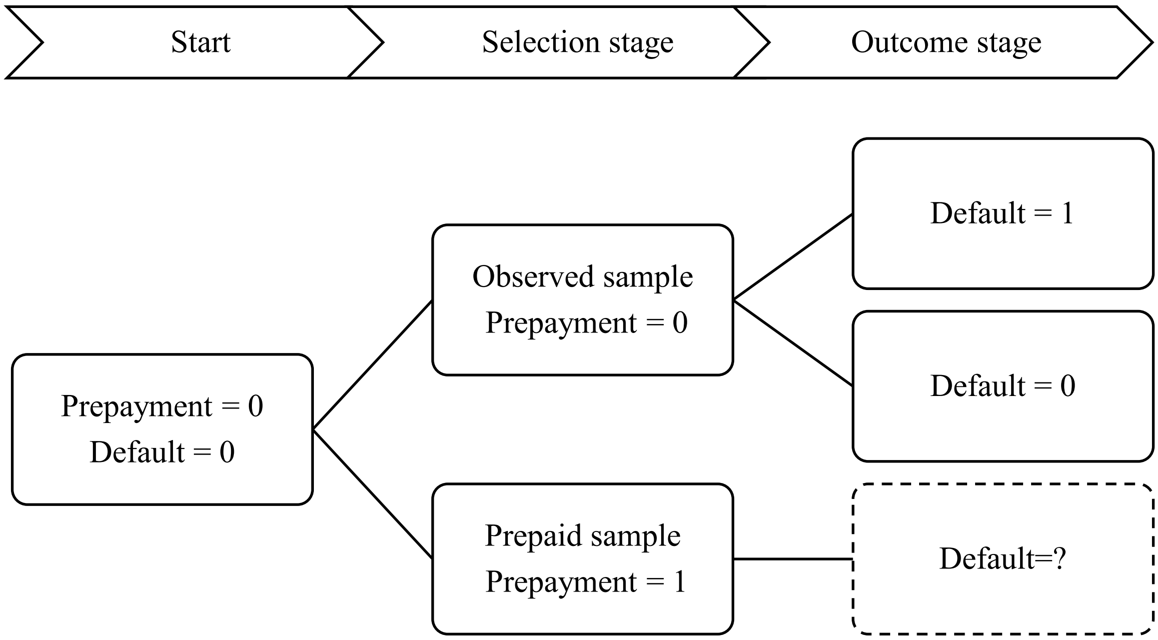

Figure 3.2. Two-stage selection mechanism

This figure shows the choice mechanism for prepayment and the subsequent outcome stage of default post-prepayment. Default is only observed for the observed sample of non-prepaid loans.

Prepayment selection divides the population into two subsamples: an observed sample and a prepaid sample. The default outcome is only known for the observed sample. The common understanding is that low credit risk borrowers are more likely to prepay while high credit risk borrowers are more likely to default. Prepayment selection then results in a higher default rate for the observed sample and a lower default rate for the prepaid sample. However, it is unclear how the default risk changes cross-sectionally in the observed sample, in particular for different levels of prepayment risks. The default indicator for payoff events can be coded as zero or missing values. I choose missing values to better align my empirical work with the simulation.

For banks, modelling default probabilities for the observed sample is a key concern as it is relevant to loan pricing, bank capital and loan loss provisioning. This is also important for the risk assessments for mortgage securitization processes. Agarwal et al. (2012) find that banks retain loans with higher default risk and lower prepayment risk in their balance sheets relative to loans they sell in secondary markets. Mortgage default risk may be affected by prepayment selection and understanding this relation is important for lenders and RMBS investors. These results are of great economic significance as mortgages are one of the most important sources of finance in the economy.

The contributions of our study are threefold. First, we investigate the relation between prepayments and defaults and decompose the impact of observed factors (unconditional effect) and correlated observed factors (selection effect). The unconditional effect results in low default risk borrowers prepaying and high risk borrowers remaining in the portfolio. The selection effect results in a higher conditional probability of default for the observed sample for high-prepayment-risk loans.[11]

Second, we study the relation between prepayments and defaults in different macroeconomic periods. We show that for economic upturns, high default risk is caused by the selection effect for borrowers who are likely to prepay/refinance but eventually do not. For economic downturns, high default is caused by the unconditional effect of risk factors, which indicates that borrowers that have a low prepayment risk are exposed to high default risk.

Third, we provide a methodological model for a two-stage model using a credit correction ratio (CCR) to achieve better calibration of PDs for the observed sample. We show that an industry model, which does not control for prepayments, overestimates the predicted PDs for low-prepayment-risk groups and underestimates the predicted PDs for high-

[11] The increase of default risk for borrowers that should have left the portfolio due to low default risk but did not do so is likely de to omitted variables (selection effect) and may explain the findings of Keys, Pope and Pope (2016) who find that 20% of unconstrained borrowers for whom refinancing was optimal had not done so.

prepayment-risk groups. Literature models (MNL model and two-stage model using IMR) are slightly better than the industry models. Our model with CCR correction term outperforms the other models.

3.2.2 Research approach

We first investigate the relation between prepayments and defaults in a simulation study where we know the data generating process. We document a u-shaped relation between default risk and prepayment risk. Default risk is high for both low and high prepayment risk. Default risk is low for medium prepayment risk. We find that two effects explain this relation: an unconditional effect based on observed risk factors explains high default rates for low-prepayment-risk loans and a selection effect based on correlated unobservable factors explains high defaults for high-prepayment-risk loans. We document that the selection effect is amplified by prepayment probabilities.

We run tests on empirical data of US prime mortgage loans by Freddie Mac from 2000 to 2016. We find that prepayments and defaults are inversely related not only for observed credit risk factors but also for correlated unobservable factors that explain the selection effect. We find a u-shaped pattern for the relation of prepayment and default rate, which is consistent with the simulation study.

Next, we investigate prepayment selection in economic upturns and downturns. Prepayments are likely to occur for economic upturns when interest rates are low and borrowers may be seeking a better contract in the marketplace. In addition, lenders often relax their lending standards for economic upturns, allowing borrowers to qualify more easily for refinance. On the other hand, high interest rates and tightened lending standards for economic downturns result in fewer prepayments and more defaults. We find that the selection effect is the main cause for high defaults in economic upturns, which indicates borrowers who have high prepayment probabilities but did not actually prepay. For economic downturns, the unconditional effect dominates the selection effect, which indicates high defaults on low-prepayment-risk borrowers.

Further, we analyze loans with different loan-to-value (LTV) ratios in different macroeconomic states. Specifically, we analyze loans with LTV below and above 80%. The LTV of 80% is a lending threshold for mortgage loans without the requirement of mortgage insurance. Prepayments are usually associated with LTVs below 80%, while defaults are usually associated with LTVs above 80%. We find that for economic upturns the selection effect is the main cause for high defaults on loans at both levels of LTV below and above 80%. For economic downturns the unconditional effect dominates on loans with LTV above 80%, implying that borrowers are likely to default because they were unable to refinance.

Lastly, we develop a method to solve the bias from prepayment selection. Industry practices commonly use single-equation models such as Logit/Probit models to predict probabilities of defaults. These models focus on default determinants (observed factors) and do not control for prepayments. The mortgage literature has considered prepayments and defaults as two competing risks, but not a selection mechanism and have commonly used multinomial Logit models (MNL). In many other applications of the sample selection, a two-stage model proposed by Heckman (1979) with a correction term of Inverse Mill Ratio (IMR) is used. The IMR is based on a first stage probability to select with the consequence to be observed. The mechanism of prepayment selection is different as a borrower decides to leave, with the consequence not to be observed. We discuss the use of correction terms and suggest that IMR is not an appropriate measure to correct the prepayment bias. We derive a new measure and call it credit correction ratio (CCR) as the situation chiefly applies to credit risk. We propose a two-stage modelling approach to estimate the conditional PD for the observed sample using CCR.

We focus on assessing the accuracy of predicted PDs post-prepayment for the empirical data. We define calibration as the property of a model's predicted PDs to match observed default rates. Default events are binary indicator variables and PDs are expectations for these events. We measure the deviation as the difference between the mean of predicted PDs and the default rate divided by the default rate. A positive deviation means an overestimation of defaults and a negative deviation means an underestimation of defaults. To measure the overall accuracy, we use the mean absolute error (MAE) measured as the mean of absolute deviations. The greater the MAE, the greater the miscalibration of a model. In particular, we assess the accuracy of an industry model without controlling for prepayment (PD_PROBIT), a literature model for competing risks (PD_MNL), a literature two-stage model using IMR (PD_IMR) and our two-stage model with a new correction term (PD_CCR). We expect that PD_CCR can capture the selection effect more efficiently and predict PDs with a greater calibration and hence accuracy.

We find that an industry model without controlling for prepayments results in an MAE of 18%, overestimates the default risk for low-prepayment-risk groups (by 21% for the bottom half of the lowest-prepayment-risk loans) and underestimates default risk for high-prepayment-risk groups (by 17% for the top half of the highest-prepayment-risk loans). Two literature models, PD_MNL and PD_IMR, are slightly better than the industry model with MAEs of 11% and 13% respectively. Our model with a novel correction term (PD_CCR) outperforms both the industry and literature models by reducing the MAE to 5%.

The paper proceeds a follows. Section 3.3 reviews the literature. Section 3.4 describes our modelling approach. Section 3.5 decomposes the combined observed prepayment effect into an unconditional effect and a selection effect using a simulation study. Section 3.6 provides analysis for empirical data on US prime mortgages and robustness checks. Section 3.7 summarizes and presents policy implications inferred from our study.

3.3 Literature review

3.3.1 Common factors of prepayments

Prepayments have been covered from a portfolio return perspective in terms of reinvestment risk for commercial banks and other mortgage investors. Literature shows that the main motivation for mortgage prepayment is refinancing when interest rates fall (Agarwal, Driscoll and Laibson, 2013; Chernov, Dunn and Longstaff., 2017). Borrowers have an incentive to reduce their monthly payments by applying for mortgages with a lower rate and prepaying the existing mortgage if market interest rates or credit spreads fall substantially (Campbell, 2006).

However, borrowers may make irrational refinancing decisions. Keys, Pope and Pope (2016) find that 20% of borrowers that appeared unconstrained to refinance failed to do so at some point during the recent decline in interest rates. Agarwal, Rosen and Yao (2015) document that more than 50% of borrowers refinance sub-optimally, either choosing the wrong rate or waiting too long to refinance. Bennett, Peach and Peristiani (2001) explain that borrowers postpone refinancing in the face of high interest rate volatility.

Credit rating and loan-to-value (LTV) ratio have significant effects on the refinancing probabilities. Bennett, Peach and Peristiani (2001) show that the better the credit rating, the higher the refinancing probabilities. In addition, borrowers applying for a refinancing loan that has LTV above 80% are usually required to take out lenders' mortgage insurances, thus less likely to refinance. In addition, if the current LTV ratio is higher than the LTV ratio at origination, borrowers have to pay a higher risk premium when refinancing (Pavlov, 2001).

Yang, Buist and Megbolugbe (1998) incorporate lending standards and find that the underwriting rules based on LTV constrains the refinancing choice. Caplin, Freeman and Tracy.

(1997) find that a decrease in property values may make it difficult for borrowers to refinance their mortgage.

Chernov, Dunn and Longstaff (2017) find that macroeconomic drivers such as house price appreciation can affect the cash-out mortgage. In that case, borrowers refinance to extract home equity. Khandani, Lo and Merton (2013) show that refinancing and cash-out can potentially cause a systemic risk in the financial system as borrowers do not increase equity levels and continue to be vulnerable to future house price falls.

Pavlov (2001) separates prepayment between refinances and moving-related house sales. The decision to move is independent of financial considerations related to the mortgage and differs from refinance. The probability to move depends on exogenous factors such as unemployment, location and economic conditions. For instance, the study shows that borrowers from high-income areas are more likely to take advantage of interest rate savings and decide to refinance, while mortgages originated in low-income areas tend to be prepaid for relocation purposes.

In short, the main drivers for prepayments are mostly related to borrower-specific, loan-specific, house-specific and macroeconomic factors. The latter include the gap in interest rates, credit ratings, loan-to-value ratios, lending standards, geographic location and house prices.

3.3.2 Common factors of the defaults

Default is triggered when borrowers cannot meet their financial obligations timely and fully. The process generally starts with borrower payment delinquency of 90 days or more. In most instances, the foreclosure process follows delinquencies. However, during the Global Financial Crisis of 2007-2009, there were instances where a credit loss occurred but no delinquency. For example, in non-recourse states, customers can effectively repay their loans by passing on the house ownership to lenders which is rational if house prices are below outstanding debt values.

A number of studies using econometric models find that borrower creditworthiness, loan-specific characteristics, collateral and the macro economy are key factor for mortgage defaults. Some studies using option-pricing models suggest that negative equity and illiquidity are the main reasons for default (Deng et al., 2000; Elul et al., 2010; and Campbell and Cocco, 2015). Campbell and Dietrich (1983) and others show that ratios of payment relative to income and the loan-to-value ratio (LTV) can predict default. Gerardi et al, (2017) analyze house price declines which result in negative equity triggering strategic defaults, as well as liquidity shock due to income losses or expense shocks. Lastly, macroeconomic variables such as the unemployment rate and GDP growth rate are important factors (Demyanyk and Van Hemert, 2009).

In short, main drivers for defaults are borrower-specific credit risk factors such as the credit score and debt-to-income ratios, loans-specific factors such as LTV ratios, collateral-specific like house valuations and macroeconomic variables.

3.3.3 Relation between prepayments and defaults

A number of studies provide evidence for the relation between prepayments and defaults events. Ciochetti et al. (2002) find a convex relation due to common factors affecting cash flows, credit histories and LTV ratios. Deng, Quigley and Van Order (2000) claim that estimating default and prepayment risks separately leads to serious errors in estimating the default risk and propose competing hazard models. However, Pavlov (2001) suggests that separating various causes of mortgage termination leads to a better understanding as determinants of refinances are different from the drivers of defaults and should be modelled with separate parameterizations.

Probit and Logit models are common in industry with the binary default indicator as the dependent variable. Survival models have been proposed but have the limitation that implied probabilities of default may not be calibrated (see Baesens et al., 2016). Djeundje and Crook (2019) show that baseline risk of survival models can be included in Probit models with loan age splines.

The literature has considered prepayments and defaults as two competing risks. Another alternative method for competing risks of mortgage termination is the Multinomial Logit (MNL) model. Pennington-Cross (2010) model multiple outcomes of loan such as prepayment, foreclosure, partial cure and cure. Agarwal et al. (2012) find an adverse selection in securitization that securitized loans have a higher prepayment risk and a lower default risk than loans on lenders' balance sheets. Those papers compare the parameter estimates but do not assess the calibration of model implied PDs.

The literature documents that a drawback of MNL model is the Independence from Irrelevant Alternatives, which requires that the odds ratio for any two alternative outcomes should be independent from other alternatives. This assumption is likely violated for mortgage loans. The bias in parameter estimates when using an MNL model may occur, depending on correlation between the omitted variables and the included variables (Lee, 1982 and McFadden, 1987).[12]

Our study is different from the literature in that we consider prepayments as a selection mechanism to the default process, hence the interaction between prepayment and default risks for mortgage loans.

[12] MNL are likely to be biased if there is a correlation between unobservable factors and observed variables coefficients.

3.3.4 Contributions of our study

The main contributions of our paper are threefold. Firstly, we investigate the relation between prepayments and defaults and decompose the impact of observed common factors (unconditional effect) and correlated observed factors (selection effect). When borrowers decide to prepay their loans, they leave the portfolio and are no longer observed by lenders. The selection effect results in a higher conditional probability of default for the observed sample for high-prepayment-risk loans.

Secondly, we study the relation between prepayments and defaults in different macroeconomic periods. We show that for economic upturns, high default risk is caused by the selection effect, which indicates borrowers who are likely to prepay/refinance but eventually do not. For economic downturns, high default is caused by the unconditional effect of common credit risk factors, which indicates that borrowers that have a high prepayment risk but do not prepay are exposed to high default risk.

Thirdly, we provide a methodological extension in a two-stage model using a credit correction ratio term (CCR) to achieve better calibration of PDs on the observed sample. We show that an industry model, which does not control for prepayments, overestimates the predicted PDs for low-prepayment-risk groups and underestimates the predicted PDs for high-prepayment-risk groups. Literature models (MNL model and two-stage model using IMR) are slightly better than the industry models. Our model with CCR correction term outperforms the industry model and the literature models.

3.4 Modelling frameworks

3.4.1 Default process without sample selection

We start with a Probit model which is commonly used to model binary outcomes. The latent process describing the borrower credit risk without considering prepayment is:

$$D_{it}^{*} = \beta_D' x_{it,D} + \varepsilon_{it,D} \tag{1}$$

In Eq (1), D_{it}^{*} is a latent variable which is driven by a linear vector of observable variables of borrower and loan specific characteristics, $x_{it,D}$, and unobservable information captured in $\varepsilon_{it,D}$, which is assumed to be standard normally distributed.[13]

A default occurs if this variable exceeds a threshold.

$$D_{it}\ (default) = \begin{cases} 1 \text{ if } \mathrm{D}_{\mathrm{it}}^{*} > 0 \\ 0 \text{ if } \mathrm{D}_{\mathrm{it}}^{*} \leq 0 \end{cases} \tag{2}$$

The threshold is arbitrary as it can be shown that different thresholds result in the same parameter estimates.[14] The default indicator, D_{it} is one for positive D_{it}^{*} and zero for negative D_{it}^{*}. We estimate the model parameters by maximizing the log likelihood:

$$\mathrm{LL} = \sum_{i=1}^{I}\sum_{t=1}^{T} \ln\left[D_{it}\mathrm{P}\left(D_{it} = 1|x_{it,D}, \beta_{\mathrm{D}}\right) + (1 - D_{it})\left(1 - \mathrm{P}\left(D_{it} = 1|x_{it,D}, \beta_{\mathrm{D}}\right)\right)\right] \tag{3}$$

The unconditional PD estimation is estimated as follows:

$$\widehat{Pr}(D_{it} = 1) = \Phi\left(\hat{\beta}_D' x_{it,D}\right) \tag{4}$$

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[13] Other distributions may be assumed. For example, a logistic distribution implies a Logit model. We have confirmed in simulations studies that Logit and Probit models are comparable in terms of the output probabilities of default (note that parameters different due to the different link functions). Results are available on request.

[14] McNeil et al. (2005) show that different thresholds will result in the same probability estimates.

In Eq (4), $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution. Eq. (4) returns the unconditional PD for the population, which depends on observed factors, $x_{it,D}$ only, if the default is observed in the whole population without selection mechanism.

3.4.2 Default process with prepayment selection

We introduce a latent prepayment process:

$$P_{it}^{*} = \beta_P' x_{it,P} + \varepsilon_{it,P} \tag{5}$$

In the Eq (15), P_{it}^{*} is a latent variable, which is estimated by a linear regression on a vector of observable variables explaining the prepayment indicator, $x_{it,P}$ and some unobserved information captured in $\varepsilon_{it,P}$, which is standard normally distributed.

A prepayment event occurs if the latent variable exceeds an arbitrary threshold:

$$P_{it}\ (payoff) = \begin{cases} 1\ if\ P_{it}^{*} > 0 \\ 0\ if\ P_{it}^{*} \leq 0 \end{cases} \tag{6}$$

In Eq (16), the prepayment indicator P_{it}, is one if P_{it}^{*} is positive and zero if P_{it}^{*} is negative. The prepayment probability is estimates by:

$$\widehat{Pr}(P_{it} = 1) = \Phi\left(\hat{\beta}_P' x_{it,P}\right) \tag{7}$$

Now assume that unobservable variables of default in Eq (1) and prepayment in Eq (5) (i.e., $\varepsilon_{it,D}\ and\ \varepsilon_{it,P}$) are correlated by ρ:

$$\begin{bmatrix} \varepsilon_{it,P} \\ \varepsilon_{it,D} \end{bmatrix} \sim \mathrm{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{8}$$

Prepayment selection divides the population into two subsamples: an observed sample ($P_{it} = 0$) and a prepaid sample ($P_{it} = 1$). We only observe the default indicator for the observed sample. We would expect a negative correlation between prepayments and defaults ($\rho < 0$) as prepayment may relate to low default risk. The prepayment selection then results in a higher default rate on the observed sample and a lower default rate on the prepaid sample.

We can generate the conditional linear predictor of default for the observed sample is:

$$\mathrm{E}\left(D_{it}^{*} \middle| x_{it,D}, P_{it} = 0\right) = \mathrm{E}\left(D_{it}^{*} \middle| x_{it,D}, P_{it}^{*} \leq 0\right) = \beta_D x_{it,D} + E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} \leq -\beta_P' x_{it,P}\right) \tag{9}$$

The conditional linear predictor of default for the prepaid sample is:

$$\mathrm{E}\left(D_{it}^{*} \middle| x_{it,D}, P_{it} = 1\right) = \mathrm{E}\left(D_{it}^{*} \middle| x_{it,D}, P_{it}^{*} > 0\right) = \beta_D x_{it,D} + E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} > -\beta_P' x_{it,P}\right) \tag{10}$$

As $\varepsilon_{it,P}$ and $\varepsilon_{it,D}$ is a bivariate normal distribution with a correlation ρ, the conditional distribution of $\varepsilon_{it,D}$ given $\varepsilon_{it,P}$ is a normal distribution with mean $\rho\mathrm{E}(\varepsilon_{it,P})$ (compare Balakrishnan, 2014). Also, using the fact that if a random variable $X \sim N(0,1)$ then $E(X|X < \alpha) = \frac{-\phi(\alpha)}{\Phi(\alpha)}$, we have a further derivation for Eq (9) as:

$$E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} \leq -\beta_P' x_{it,P}\right) = \rho E\left(\varepsilon_{it,P} \middle| \varepsilon_{it,P} \leq -\beta_P' x_{it,P}\right) = \rho \frac{-\phi(-\beta_P' x_{it,P})}{\Phi(-\widehat{\beta_P'} x_{it,P})} = \rho \frac{-\phi(\beta_P' x_{it,P})}{1-\Phi(\widehat{\beta_P'} x_{it,P})} \tag{11}$$

Similarly, using the fact that $E(X|X > \alpha) = \frac{\phi(\alpha)}{1-\Phi(\alpha)}$ we can derive further for Eq (10) as:

$$E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} > -\beta_P' x_{it,P}\right) = \rho E\left(\varepsilon_{it,P} \middle| \varepsilon_{it,P} > -\beta_P' x_{it,P}\right) = \rho \frac{\phi(-\beta_P' x_{it,P})}{1-\Phi(-\widehat{\beta_P'} x_{it,P})} = \rho \frac{\phi(\beta_P' x_{it,P})}{\Phi(\widehat{\beta_P'} x_{it,P})} \tag{12}$$

Substitute Eq (11) into Eq (9), we have the conditional PD for the observed sample:

$$\Pr(D_{it} = 1|P_{it} = 0) = \Phi\left(\beta_D' x_{it,D} + \rho \frac{-\phi(\beta_P' x_{it,P})}{1-\Phi(\widehat{\beta_P'} x_{it,P})}\right) \tag{13}$$

Substitute Eq (12) into Eq (10), we have the conditional PD for the prepaid sample is:

$$\Pr(D_{it} = 1|P_{it} = 1) = \Phi\left(\beta_D' x_{it,D} + \rho \frac{\phi(\beta_P' x_{it,P})}{\Phi(\widehat{\beta_P'} x_{it,P})}\right) \tag{14}$$

In Eq (13) and Eq (14), $\phi(.)$ is the probability density function (PDF) and $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution.

Eq (13) and Eq (14) demonstrate the significant differences between correction terms in the prepayment selection and Heckman selection.

In Eq (13), the part $\rho \frac{-\phi(\beta_P' x_{it,P})}{1-\Phi(\widehat{\beta_P'} x_{it,P})}$ is the estimate for $E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} \leq \beta_P' x_{it,P}\right)$ in Eq (9). We compute the credit correction ratio $CCR = \frac{-\phi(\widehat{\beta_P'} x_{it,P})}{1-\Phi(\widehat{\beta_P'} x_{it,P})}$ as the ratio to measure omitted variables derived from prepayment process. CCR is negative and is calculated as the probability of prepayment over the cumulative probability of non-prepayments.

In Eq (14), the part $\rho \frac{\phi(\beta_P' x_{it,P})}{\Phi(\widehat{\beta_P'} x_{it,P})}$ is the estimate for $E\left(\varepsilon_{it,D} \middle| \varepsilon_{it,P} > -\beta_P' x_{it,P}\right)$ in Eq (10). The Inverse Mills ratio $IMR = \frac{\phi(\beta_P' x_{it,P})}{\Phi(\widehat{\beta_P'} x_{it,P})}$ is always positive, which implies the inclusion of prepayments into the prepaid sample. It is calculated as a probability of prepayment over the cumulative probability of prepayments.

As we are looking at non-prepayment events for the selection mechanism, we use ratio CCR rather than the IMR in the observed sample. Puhani (2000) documents that a Heckman model using IMR does not provide an improvement in predictive power relative to a regression on the observed sample.

The literatures in the mortgage space have considered prepayment as a competing risk to default, not a selection mechanism. The intuition of a competing risks model is that a borrower can have a “choice” of prepayment or default, or neither, depending on a utility that he or she receives for each option. To control for competing risks, Pennington-Cross (2010) and Agarwal, Chang and Yavas (2012) use multinomial Logit models (MNL).15 We also run MNL models in our empirical data and note that the accuracy is worse than our suggested approach of a two-stage model described in the following section.

3.4.3 Two-stage default model with prepayment correction

The main contributions in terms of methodology in our approach are twofold. Firstly, we have developed the correction term in a selection mechanism from which a population is selecting out of. We construct a two-stage model to estimate the conditional PD on the observed sample. In our subsequent empirical analysis, we also compare our approach with the MNL model for competing risks and find that our model performs better, even though two mechanisms (competing risks and selection) are different.

We develop a two-stage statistical model for prepayments and defaults as follows:

- Stage 1: Prepayment model

$$\Pr((P_{it} = 1) = \Pr(\beta_P' x_{it,P} + \varepsilon_{it,P} > 0) \tag{15}$$

[15] We describe the modelling approach for the Multinomial Logit (MNL) model in the Internet Appendix.

In this state, prepayment is estimated on the population and we will obtain the parameter estimates $\widehat{\beta'_P}$. Each loan in the population can be assigned a prepayment probability estimated by Eq (7) using the Probit function.

At the end of stage 1, we can calculate ratio $CCR = \frac{-\phi(\widehat{\beta'_P} x_{it,P})}{1-\Phi(\widehat{\beta'_P} x_{it,P})}$ for Stage 2.

- Stage 2: Conditional default model on the observed sample

As the default indicator is known for the observed sample only we estimate a default model on the observed sample ($P_{it} = 0$) including the correction term CR into the model.

$$\Pr(D_{it} = 1 | P_{it} = 0) = \Pr(\beta'_{Ob} x_{it,D} + \delta CR + u_{it,D} > 0) \quad (16)$$

In Eq (16), the error $u_{it,D}$ is standard normally distributed. The conditional PD on the observed sample is:

$$\widehat{\Pr}\ (D_{it} = 1 | P_{it} = 0) = \Phi\left(\widehat{\beta'_{Ob}} x_{it,D} + \hat{\delta} CR\right) \quad (17)$$

In Eq (17), $\widehat{\beta'_{Ob}}$ is a vector of parameter estimates for a vector of observed variables, $x_{it,D}$ for the observed sample and $\hat{\delta}$ is the estimate for the correction term CCR .

Assuming a selection mechanism that low risk borrowers will prepay and high risk borrower will default, we expect a negative value for $\hat{\delta}$. Thus, the linear predictor of default on the observed sample ($\widehat{\beta'_{Ob}} x_{it,D} + \hat{\delta} CR$) is greater than the unbiased linear predictor ($\widehat{\beta'_D} x_{it,D}$) in the unconditional PD by Eq (4) as CCR is always negative. As a result, we expect that the conditional PD on the observed sample by Eq (17) is higher than the unconditional PD by Eq (4). This result makes sense with the assumption that low risk borrowers leave and high risk ones remain the observation sample.

3.5 Decomposition of observed effect

3.5.1 Unconditional effect and selection effect

We decompose the observed effect by disentangling the effects of observed factors (unconditional effect) and unobservable factors (selection effect) on default in a formula-based proof. In addition, the selection effect is amplified by prepayment probabilities where for a higher prepayment probability the impact of selection is greater. We illustrate this finding in a simulation study which is described in the next section.

The observed effect is the conditional PD on the observed sample, which is estimated by Eq (13) and is specified as $PD_{it,Ob}$. The unconditional effect is the unconditional PD on the population estimated by Eq (4) and is $PD_{it,\mathrm{Un}}$.

The selection effect is the difference between the observed effect and the unconditional effect.

$$\text{Selection effect} = PD_{it,Ob} - PD_{it,Un} \tag{18}$$

Now, the unconditional PD on the population, which depends on observed factors, $x_{it,D}$ only can be written as:

$$PD_{it,Un} = PD_{it,\mathrm{Ob}} * (1 - PP_{it}) + PD_{it,Pr} * PP_{it} \tag{19}$$

In Eq (19), $PD_{it,\mathrm{Ob}}$ is the conditional PD on the observed sample(13) , $PD_{it,Pr}$ is the conditional PD on the prepaid sample by Eq (14), and PP_{it} is the prepayment probabilities. The first component $PD_{it,Ob} * (1 - PP_{it})$ is the adjusted probability of default for remaining loans, which represents the contribution of defaults from the observed sample to the population. The second component $PD_{it,Pr} * PP_{it}$ is the adjusted probability of default for prepaid loans, which represents the contribution of defaults from the prepaid sample to the population.

Substitute Eq (19) into Eq (18), we have:

$$\text{Selection effect} = PD_{it,Ob} - PD_{it,Un} = PD_{it,Ob} - PD_{it,Ob} * (1 - PP_{it}) - PD_{it,Pr} * PP_{it}$$

$$= \left(PD_{it,Ob} - PD_{it,Pr}\right) * PP_{it}$$

$$= \left(\Phi\left(\beta_D' x_{it,D} + \rho \frac{-\phi(\beta_P' x_{it,P})}{1-\Phi(\widehat{\beta_P'} x_{it,P})}\right) - \Phi\left(\beta_D' x_{it,D} + \rho \frac{\phi(\beta_P' x_{it,P})}{\Phi(\widehat{\beta_P'} x_{it,P})}\right)\right) * \ PP_{it} \quad (20)$$

The Eq (20) provides two important insights. First, the selection effect only exists if there is a correlation of unobservable factors between prepayments and defaults. This condition implies the non-randomness of the selection mechanism. Indeed, when the correlation of unobservable factors is zero ($\rho = 0$), the unconditional PDs on the observed sample and on the prepaid sample are the same and no selection effect exists. Second, the prepayment probability amplifies the selection effect. The impact of selection effect is higher for subsamples with higher prepayment probabilities. In the empirical analysis section later, we will show that the selection effect significantly changes the default outcomes of a mortgage portfolio for subsamples of high-prepayment-risk loans, rather than low-prepayment-risk loans.

3.5.2 Simulation study

3.5.2.1 Data generating process and model set up

We simulate the prepayment process by assuming set parameters $\alpha_P, \beta_P,$ and γ_P and drawing the standard normally distributed and commonly independent variables $x_{i,P}, z$ and $\varepsilon_{i,P}$ randomly:

$$P_i^* = \alpha_P + \beta_P x_{i,P} + \gamma_P z + \varepsilon_{i,P}$$

P_i^* is the latent variable for the prepayment process, $x_{i,P}$ is a borrower-specific variable and z is a systematic (e.g., macro-economic) variable explaining prepayment with coefficients β_P and γ_P. The intercept α_P represents the baseline level of the prepayment rate. The unobservable factors for prepayment are captured in error term $\varepsilon_{i,P}$.

We simulate the default process by assuming set parameters $\alpha_D, \beta_D,$ and γ_D and drawing the variables $x_{i,D}$ and $\varepsilon_{i,D}$ randomly:

$$D_i^* = \alpha_D + \beta_D x_{i,D} + \gamma_D z + \varepsilon_{i,D}$$

D_i^* is the latent variable for default process, $x_{i,D}$ is a borrower-specific variable and z is a systematic (e.g., macro-economic) variable explaining default with coefficients β_D and γ_D. The intercept α_D, represents the baseline level of the default rate. The unobservable factors for default are captured in error term $\varepsilon_{i,D}$.

We assume the correlation structure of the residuals of the prepayments and defaults processes as follows:

$$\begin{bmatrix} \varepsilon_{i,P} \\ \varepsilon_{i,D} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

All other random variables are independent. Prepayment and default indicators are determined by the following thresholds:

$$P_i\ (payoff) = \begin{cases} 1 \text{ if } \mathrm{P_i^*} > 0 \\ 0 \text{ if } \mathrm{P_i^*} \leq 0 \end{cases}$$

$$D_i\ (default) = \begin{cases} 1 & \text{if } \mathrm{P_i} = 0 \text{ and } \mathrm{D_i^*} > 0 \\ 0 & \text{if } \mathrm{P_i} = 0 \text{ and } \mathrm{D_i^*} \leq 0 \\ \text{missing value i} & \text{if } \mathrm{P_i} = 1 \end{cases}$$

Note that thresholds are arbitrary and it can be shown that different thresholds result in the same prepayments and defaults probabilities.[16]

The unconditional PD on the population from default process is:

$$\widehat{\Pr}(\, D_i^* > 0) = \Phi\big(\alpha_D + \beta_D x_{i,D} + \gamma_D z\big)$$

We apply the following parameter settings:

$$\alpha_P = -1 \qquad \beta_P = -1 \qquad \gamma_P = -0.5$$

$$\alpha_D = -3 \qquad \beta_D = -1 \qquad \gamma_D = 0.5$$

We generate two populations with different correlations of unobservable factors. The first population has one million observations with the prepayment rate of 25%, the unconditional default rate on the population of 2.3%. The conditional default rate on the observed sample is 3% and the conditional default rate on the prepaid sample is 0.08% if the correlation of unobservable factor is $\rho = -1,$.

The second population also has the same size, same prepayment and same unconditional default rate on the population as the first population. The only difference is the independent unobservable factors with $\rho = 0$. The conditional default rate for the observed sample is 2.5% and the conditional default rate for the prepaid sample is 1.6%.

[16] Compare Footnote 4 on the equivalence of alternative threshold assumptions.

We show the two extreme cases with $\rho = -1$ and $\rho = 0$, but we have tested on simulated populations with different correlations and prepayment rates[17]. All findings are consistent. In reality we would expect a correlation of unobservable factors between -1 and 0.

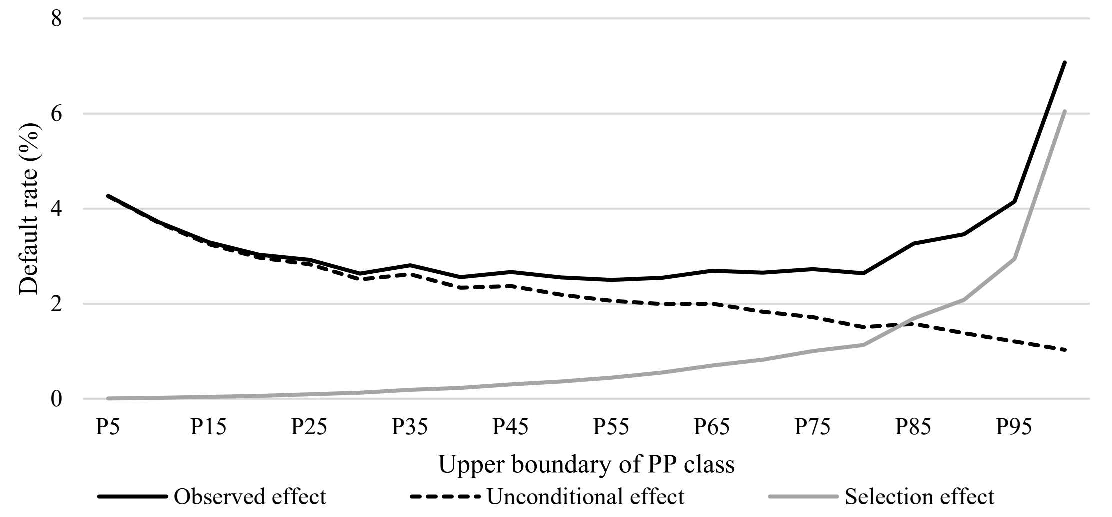
3.5.2.2 Results

To investigate the impact of prepayment selection on defaults, we first run the Stage 1 of prepayment model on the entire population of one million observations to receive the prepayment probabilities (PP) for each borrower. Next, we rank the PPs into 20 PP classes equivalent to five percent of the total observations.

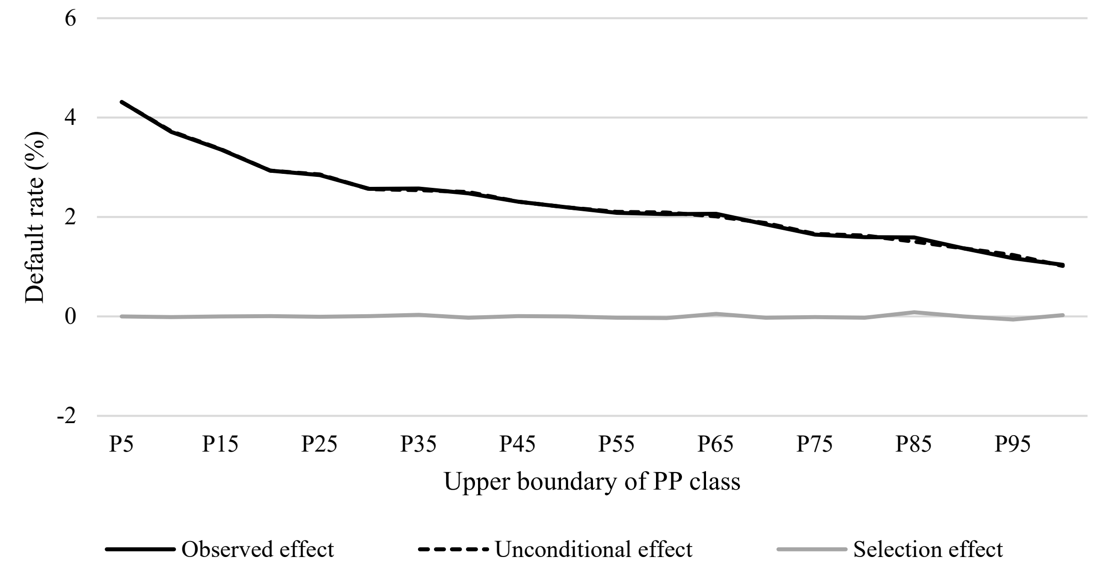
Figure 3.3 plots the mean of default rates across PP classes in the. The x-axis labels P. are the percentile rank of the upper boundary of the PP class. All PP classes throughout this paper are generated using this approach, which has the benefit of equal size in each class and a sufficiently large number of default events in all PP classes.

The solid black line is the default rates on the observed sample post-prepayment, which is defined as the observed effect. The dashed black line represents the default rates on the entire population, which is defined as the unconditional effect. This is the effect without prepayment selection as the default rate is calculated on the entire population and only depends on observed risk factors. The solid grey line is the difference between the observed effect and the unconditional effect, which is defined as the selection effect.

[17] Results are available on request.



(a) $\rho = -1$



(b) $\rho = 0$

Figure 3.3. Simulation: unconditional effect, observed effect and selection effect

This figure shows the relation between prepayments and defaults for 20 classes in our simulation study. The Figure 3a shows the relation between prepayments and defaults for a population with correlated unobservable factors (ρ=-1). Figure 3b shows the relation between prepayments and defaults for a population with independent unobservable factors (ρ=0). PP classes are defined as 5% intervals with regard the percentile rank of PP_PROBIT. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

For the first population with $\rho = -1$, the observed effect follows a u-shaped pattern in which high-default-risk groups belong to two tails of PP classes (bottom and top P5). The unconditional effect decreases across the PP class, as a result of the impact of observed factors ($x_{i,P}$, $x_{i,D}$ and opposite signs of z). The selection effect increases across the PP class as prepayment probabilities amplify the bias (see the proof in section 3.5).

For the second population with $\rho = 0$, the observed effect and the unconditional effect are similar and the selection effect is zero across all PP classes.

3.6 Empirical analysis

3.6.1 Data description

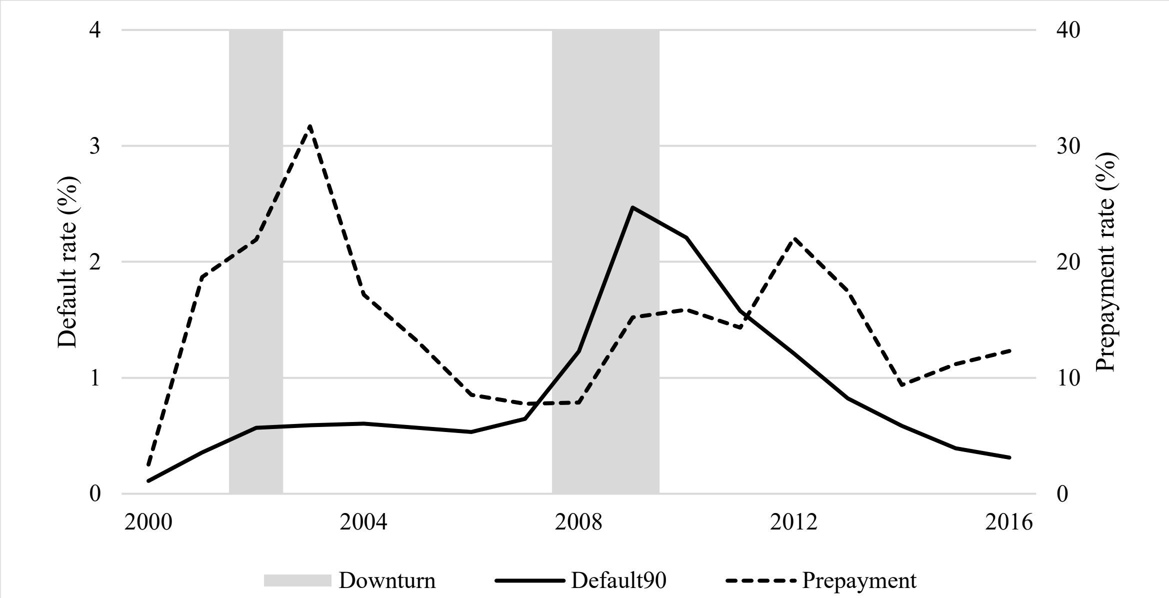
We analyze loan-level data of fixed-rate mortgages provided by the US Federal Home Loan Mortgage Corporation. All loans in our data are fixed rate mortgages originated from 2000 to 2016, and observed annually until 2016. The sample period in our paper allows us to observe a full economic cycle by accounting for the period before the GFC, during the GFC from 2007 to 2009 and after the GFC. The sample includes approximately 23 million loan accounts and 100 million observations for the entire observation period 2000 – 2016. We have used high performance cluster computing to work on the large dataset.

Beside the main mortgage dataset, we also use the house price index at zip code level from Zillow[18], the market interest rate of 30-year fixed-rate mortgages from Freddie Mac and the net percentage of domestic respondents tightening standards for mortgage loans by the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices.

[18] We have further tested the FHFA house price index (including the 3-digit, 5-digit Zip Code HPI which should be considered as experimental or developmental), as well as the Case Shiller house price index with consistent results. Results are available on request.

3.6.1.1 Dependent variables

The two dependent variables in our study are the binary prepayment and default indicators. The prepayment indicator (PREPAYMENT) takes the value of one if a loan outstanding is paid off in full and zero otherwise. The default indicator (DEFAULT90) takes the value of one if a loan is 90+ days overdue or in foreclosure.[19] Most importantly, if the prepayment indicator is one, the value of the default indicator is missing/null, meaning that we cannot observe the default status of prepaid loans. Figure 3.4 shows the prepayment rate and default rate over time. The grey bar represents the economic downturns followed by the National Bureau of Economic Research (NBER).



(a)

[19] We have also tested default definitions of 60+ days and 180+ days as robustness checks and the findings are consistent. See Section 5.2.6.

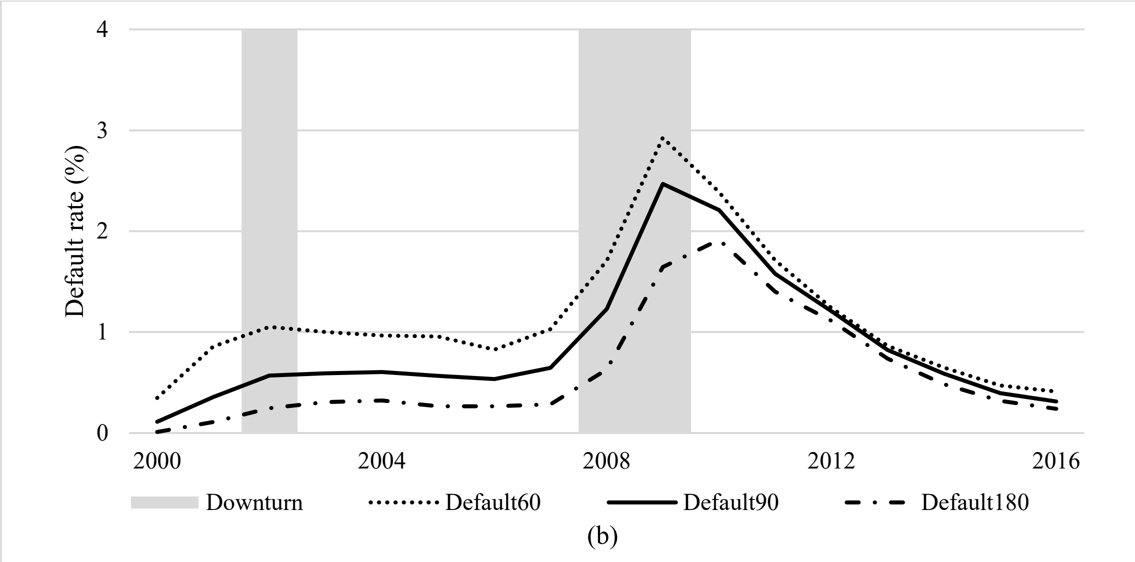


Figure 3.4. Empirical data: prepayment and default rate over time

This figure shows the annual prepayment rate and default rate of the US prime mortgages from 2000 to 2016. Figure 4a shows the prepayment rate (Prepayment) as the dashed line relative to the default rate (DEFAULT90) as the solid line. Figure 4b shows different proxies for the default indicator for a loan is in 60+/ 90+/ 180+ days past due or in foreclosure. The grey bar represents the economic downturns followed by the National Bureau of Economic Research (NBER).

Figure 3.4a shows the pattern of annual prepayments and defaults rates from 2000 to 2016. The grey bar indicates the economic downturns period documented by The National Bureau of Economic Research (NBER). In the period with high prepayment rate, the default rate was low and vice versa. The prepayment rate peaked in 2003 with over 30% per year, while the average prepayment rate across the observation period is 15% per year. The default rate peaked during the GFC with 2.5% in 2009, while the average default rate across the whole observation period is 1.0%.

Figure 3.4b shows different proxies of default indicator if a loan is in 60+ (DEFAULT60)/ 90+ (DEFAULT90)/ 180+ (DEFAULT180) days past due or in foreclosure. All default proxies are comparable in terms of their time variation. Note that a delinquency of a certain number of days was preceded by a delinquency of a lower number of days. Hence, the highest averaged default rate is 1.5% for DEFAULT60, followed by the average of DEFAULT90 at 1.2% and the lowest is 0.8% for Defaut180.

3.6.1.2 Risk factors

We include borrower-specific, loan-specific and macroeconomic risk factors as in . The variables are defined in Table 3.1.

Table 3.1 Definition of variables

This table shows the definitions of variables used in the study of prepayment selection.

Panel A: Dependent variables	
Prepayment	Dummy variable is one if a loan is prepaid fully its outstanding balance before the maturity and zero otherwise.
DEFAULT60	Dummy variable is one if a loan is in past due for 60+ days or in foreclosure and zero otherwise.
DEFAULT90	Dummy variable is one if a loan is in past due for 90+ days or in foreclosure and zero otherwise.
DEFAULT180	Dummy variable is one if a loan is in past due for 180+ days or in foreclosure and zero otherwise.
Panel B: Control variables	
Borrower-specific	
FICO	Credit score at origination that measures the credit quality of a borrower.
DTI	Debt-to-income ratio at origination that is calculated as monthly loan payment divided by monthly income.
JOINT	Dummy variable is one if a loan has multiple borrowers and zero otherwise.
Loan-specific	
LTV	Current loan-to-value ratio that is current loan outstanding relative to the current property value.
LTV_CHANGE	Difference between current loan-to-value ratio and original loan-to-value ratio.
LOAN_SIZE	Natural logarithm of the current loan amount.
TSO	Time since origination to observation date, in years.
TSO^2	Time since origination to the power of two, in years^2.
TSO^3	Time since origination to the power of three, in years^3.
INITIAL3Y	Dummy variable is one if TSO is less than three years and zero otherwise.
INVESTOR	Dummy variable is one if a loan funds an investment property and zero otherwise.
REFINANCE	Dummy variable is one if a loan was for refinance purposes and zero otherwise.
LMI	Dummy variable is one if a loan is insured by lenders' mortgage insurance and zero otherwise.
MSA	Dummy variable is one if a property is located at a metropolitan area and zero otherwise.

Systematic/macro-economic		
	HPI	Current growth rate of house price index at the zip code level from Zillow.
	LENDING_STD	Net percentage of domestic respondents tightening standards for mortgage loans by the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices.
	IR_GAP	Difference between current interest rate and market interest rate of fixed-rate mortgage.

For prepayments, the ability to refinance is generally aligned with low credit risk. The FICO score at origination is an index to capture the credit quality of borrowers. The higher the FICO score, the higher the chance of prepayment. Next, debt-to-income (DTI) at origination is a ratio between monthly debt payments and monthly income, which is a proxy for loan serviceability. The higher the DTI, the lower the chance of prepayment. For loan specific variables, a key variable is the current loan-to-value (LTV) based on the current outstanding loan amount and the current house value. We approximate the current house price using a house price index at the zip code level from Zillow. LTV is an important factor as borrowers pay higher rates for higher LTV loans. We create a variable, LTV_CHANGE, which measures the difference between current LTV and original LTV. Specifically, a borrower has easier access to refinance if the current LTV is lower than the original LTV (i.e., LTV_CHANGE>0). We include a dummy variable, LMI that is one if a loan is required to pay a lenders' mortgage insurance and zero otherwise. Another key factor that triggers the refinancing decision is the gap between current interest rate charged and the market reference rate (IR_GAP). Borrowers have a greater incentive to refinance if the gap interest rate is greater. In addition, prepayments are affected by the credit supply. We include a proxy of lending standards (LENDING_STD) measured as the net percentage of domestic respondents tightening standards for mortgage loans by the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices to control for the credit supply.

For defaults, loan specific variables such as FICO, DTI and LTV have opposite effects for defaults than for prepayments. In particular, a higher FICO score implies that borrowers have a lower probability of default. The higher the DTI and/or the higher the LTV, the higher the default risk of borrowers.

Further, we control for borrower type for both processes. The dummy variable, JOINT is one if a loan has multiple borrowers and zero if only single borrower. We also control for the loan size (LOAN_SIZE) and the loan age (time since origination, TSO). In particular, we include loan age square (TSO^2) and loan age cube (TSO^3) as controls to model the baseline hazard over mortgage lifetime. This approach is common in survival models, but can also be included in time-discrete hazard models, including Probit models (Djeundje and Crook, 2019). These terms reflect information that changes over the life of a loan and is not captured by other covariates. We also tried the natural logarithm of loan age, loan age square and loan age cube with consistent results. We create a dummy variable, INITIAL3Y to indicate whether a loan is in the first three years since origination. To control for the loan purpose, we generate a dummy variable, INVESTOR that is one if loans are for refinancing purposes and zero if loans are for primary house purchases. We also include a dummy variable, REFINANCE taking value of one if a refinancing loan and zero if a primary purchase loan. We control for the locations of properties by a dummy variable, MSA that is one if a property is located at a metropolitan area and zero otherwise. For macroeconomic variables, we use the growth of house price index using Zillow data (HPI) at the zip code level. In the period of high house price growth, we observe high prepayment rates and low default rates, and vice versa.

We do not include the gap interest rate, IR_GAP in the default models as this variable is a strong predictor for prepayment but not default. We also do not include LENDING_STD in the default models as lending standards may indirectly affect defaults through prepayments, in the way that a borrower who is defaulting often defauls because he/she could not prepay. Mayer et al. (2013) find that refinancing is particularly beneficial to riskier borrowers as it helps to lower the interest payment and then reduce defaults. Interest rate gaps and lending standards at origination may be important and we control for these by vintage dummies.

Table 3.2 provides summary statistics of variables used for the pooled data. We observe a panel of approximately 23 million loans originated and observed between 2000 and 2016 in annual frequency, resulting in over 100 million observations.[20] Loans are generally observed over multiple years.

[20] Panel data is used in many practical applications where a one period (e.g., one year) default probability is required. Examples are Basel III capital calculation and IFRS 9 (Stage I) loan loss provisioning.

Table 3.2 Summary statistics of variables on the pooled data

This table reports the mean and standard deviation of variables for the pooled panel data from 2000 to 2016 for dependent variables (PREPAYMENTs and DEFAULTS90) and control variables.

	PREPAYMENT=1		DEFAULT90=1		Difference	Pooled data	
	Mean	SD	Mean	SD		Mean	SD
PREPAYMENT (%)	100.00	(0.00)	0.00	(0.00)		14.50	(35.21)
DEFAULT90 (%)	.	.	100.00	(0.00)		1.19	(10.84)
FICO	735.55	(53.99)	685.45	(55.99)	50.10***	734.57	(55.22)
DTI (%)	33.61	(11.71)	38.94	(11.46)	-5.33***	33.64	(11.70)
JOINT_BORRS (%)	61.32	(48.70)	42.20	(49.39)	19.12***	57.68	(49.41)
LTV_TIME (%)	64.15	(21.62)	86.18	(27.73)	-22.03***	65.61	(22.01)
CHANGE_LTV (%)	-8.21	(15.39)	6.44	(24.61)	-14.65***	-6.76	(15.00)
LOAN_SIZE	11.86	(0.74)	11.84	(0.60)	0.02***	11.84	(0.63)
TSO (YEARS)	3.48	(2.71)	4.55	(2.66)	-1.07***	3.26	(2.78)
INITIAL3Y (%)	56.16	(49.62)	33.11	(47.06)	23.05***	57.79	(49.39)
OCCPY_INVEST (%)	4.40	(20.50)	5.76	(23.30)	-1.36***	5.38	(22.57)
REFINANCE (%)	61.31	(48.70)	64.60	(47.82)	-3.29***	63.22	(48.22)
LMI (%)	17.03	(37.59)	31.69	(46.53)	-14.66***	17.70	(38.16)
MSA (%)	86.37	(34.31)	84.82	(35.88)	1.55***	85.19	(35.52)
HPI_ZILLOW (%)	3.31	(9.72)	-0.84	(9.50)	4.15***	2.31	(8.99)
LENDING_STD (%)	4.44	(18.36)	12.06	(21.76)	-7.62***	7.02	(22.12)
GAP_IR (%)	0.99	(0.91)	1.26	(1.38)	-0.27***	0.60	(1.04)
Obs	14,738,813		1,033,625			101,619,855	

Note: Standard deviations are presented in parentheses * p =0.1, ** p = 0.5, *** p = 0.01.

The average prepayment rate is 14.5% per year and the default rate is 1.2% per year. The descriptive statistics suggest that prepayments and defaults often have opposite relations to control variables. We provide tests for mean comparison of control variables between prepayments and defaults and all variables are significantly different between the two groups. For instance, the average FICO score is 736 for prepaid borrowers and 685 for defaulted borrowers; the average current LTV (LTV) is 64% for prepaid borrowers and 86% for defaulted borrowers. Looking at macroeconomic variables, at the time of prepayment events the annual growth of house price index (HPI) is 3.3% and at the time of default is -0.84%.

Table 3.3 provides summary statistics for economic upturns and downturns. We define economic upturns from 2000 to 2006 and economic downturns from 2007 to 2009. For economic upturns, prepayment rate is 17.5%, which is higher prepayment rate of 10.5% for economic downturns. The default rate for economic upturns is 0.66%, which is lower than the default rate of 1.72% for economic downturns. All other control variables are significantly different between the two regimes.

Loans with LTV (ratios) below 80% have a higher prepayment rate and a lower default rate. However, the differences of prepayment rate/default rate between LTV below 80% and above 80% for economic upturns is relatively smaller than for economic downturns. For instance, the difference of default rate for two LTV buckets is -0.5% for economic upturns and is 2.7% for economic downturns. All other control variables are significantly different between the two LTV buckets.

Table 3.3 Summary statistics of variables on subsamples with LTV below and above 80% in upturns and downturns

This table reports the mean and standard deviation of dependent variables (PREPAYMENT and DEFAULTS90) and control variables by LTV levels below and above 80% in sub-periods. Economic upturns are from 2000 to 2006. Economic downturns are from 2007 to 2009.

	Upturns						Downturns					
	LTV<=80		LTV>80		All		LTV<=80		LTV>80		All	
PREPAYMENT (%)	17.81	(38.26)	15.82	(36.49)	17.45	(37.95)	11.41	(31.80)	8.62	(28.07)	10.61	(30.80)
DEFAULT90 (%)	0.57	(7.55)	1.04	(10.13)	0.66	(8.09)	0.92	(9.55)	3.63	(18.70)	1.72	(13.00)
FICO	721.89	(55.89)	704.12	(54.03)	718.66	(55.98)	731.72	(56.18)	720.84	(54.27)	728.59	(55.86)
DTI (%)	33.02	(12.07)	36.08	(10.37)	33.58	(11.84)	33.34	(12.55)	37.63	(11.36)	34.58	(12.37)
JOINT (%)	61.13	-48.75	57.37	(49.45)	60.45	(48.90)	59.61	(49.07)	53.77	(49.86)	57.93	(49.37)
LTV (%)	59.99	(15.34)	87.66	(5.35)	65.01	(17.65)	58.08	(15.96)	93.57	(13.69)	68.30	(22.22)
LTV_CHANGE (%)	-10.76	(10.04)	-4.41	(4.87)	-9.60	(9.64)	-9.04	(12.40)	7.57	(14.88)	-4.26	(15.16)
LOAN_SIZE	11.79	(0.53)	11.78	(0.48)	11.79	(0.52)	11.78	(0.61)	12.04	(0.51)	11.85	(0.59)
TSO (years)	1.68	(1.19)	1.03	(0.80)	1.56	(1.16)	3.41	(2.10)	2.27	(1.51)	3.08	(2.01)
INITIAL3Y (%)	85.10	(35.61)	97.30	(16.22)	87.31	(33.29)	44.96	(49.75)	71.78	(45.01)	52.69	(49.93)
INVESTOR (%)	4.76	(21.29)	2.66	(16.10)	4.38	(20.47)	4.94	(21.66)	4.45	(20.62)	4.80	(21.37)
REFINANCE (%)	65.96	(47.38)	32.72	(46.92)	59.93	(49.00)	68.60	(46.41)	43.97	(49.63)	61.51	(48.66)
LMI (%)	11.18	(31.51)	71.67	(45.06)	22.15	(41.53)	9.27	(29.00)	34.20	(47.44)	16.45	(37.07)
MSA (%)	85.57	(35.14)	83.11	(37.46)	85.13	(35.58)	83.16	(37.43)	87.12	(33.50)	84.30	(36.38)
HPI (%)	7.75	(8.65)	5.28	(7.63)	7.30	(8.53)	-3.58	(11.11)	-5.31	(9.55)	-4.08	(10.71)
LENDING_STD (%)	1.35	(4.29)	2.30	(4.33)	1.52	(4.31)	43.89	(18.57)	43.71	(19.79)	43.84	(18.93)
IR_GAP (%)	0.22	(0.79)	0.40	(0.79)	0.26	(0.79)	0.45	(0.74)	0.81	(0.76)	0.55	(0.76)
Obs	20,766,160		4,603,401		25,369,561		15,472,656		6,258,433		21,731,089	

3.6.2 Multivariate regression models

3.6.2.1 Pooled data

Table 3.4 shows regression results on the pooled panel data from 2000 to 2016.

Table 3.4 Regression results on pooled data

This table reports the regression results for prepayment and default models for the pooled data. PP_PROBIT and PP_MNL represent prepayment regressions for a two-stage model and a multinomial Logit model respectively. PD_Probit, PD_MNL, PD_IMR and PD_CCR are default regressions using a Probit model, a multinomial Logit model, a two-stage model using IMR correction term and a two-stage model using CCR correction term respectively.

	PP_PROBIT	PP_MNL	PD_Probit	PD_MNL	PD_IMR	PD_CCR
FICO	0.0007***	0.0013***	-0.0046***	-0.0100***	-0.0046***	-0.0046***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
DTI	-0.0006***	-0.0013***	0.0079***	0.0199***	0.0079***	0.0077***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
JOINT	0.1112***	0.2035***	-0.2218***	-0.5118***	-0.2304***	-0.2419***
	(0.0003)	(0.0006)	(0.0009)	(0.0021)	(0.0009)	(0.0009)
LTV	-0.0030***	-0.0053***	0.0104***	0.0249***	0.0105***	0.0106***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
LTV_CHANGE	-0.0101***	-0.0184***	0.0028***	0.0000	0.0034***	0.0038***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
LOAN_SIZE	0.1687***	0.3302***	-0.0181***	0.0404***	-0.0224***	-0.0271***
	(0.0003)	(0.0006)	(0.0009)	(0.0022)	(0.0009)	(0.0009)
TSO	0.1778***	0.3064***	0.4274***	1.0432***	0.3837***	0.3451***
	(0.0004)	(0.0007)	(0.0013)	(0.0033)	(0.0012)	(0.0014)
TSO2	-0.0306***	-0.0536***	-0.0547***	-0.1383***	-0.0492***	-0.0447***
	(0.0001)	(0.0001)	(0.0002)	(0.0005)	(0.0002)	(0.0002)
TSO3	0.0010***	0.0017***	0.0022***	0.0055***	0.0020***	0.0018***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
INITIAL3Y	0.2643***	0.4813***	0.1227***	0.3498***	0.0840***	0.0504***
	(0.0006)	(0.0012)	(0.0018)	(0.0044)	(0.0017)	(0.0018)
Investor	-0.3534***	-0.6654***	0.1261***	0.1839***	0.1346***	0.1466***
	(0.0008)	(0.0015)	(0.0018)	(0.0046)	(0.0019)	(0.0019)
REFINANCE	-0.0214***	-0.0367***	0.1384***	0.3807***	0.1450***	0.1536***
	(0.0004)	(0.0007)	(0.0010)	(0.0024)	(0.0010)	(0.0010)
LMI	-0.0833***	-0.1523***	0.1019***	0.2049***	0.1069***	0.1107***
	(0.0005)	(0.0009)	(0.0012)	(0.0028)	(0.0012)	(0.0012)
MSA	0.0754***	0.1457***	-0.0409***	-0.0679***	-0.0455***	-0.0511***
	(0.0005)	(0.0009)	(0.0012)	(0.0029)	(0.0012)	(0.0012)
HPI	0.0022***	0.0043***	-0.0047***	-0.0103***	-0.0055***	-0.0073***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
LENDING_STD	-0.0035***	-0.0067***		0.0037***		
	(0.0000)	(0.0000)		(0.0000)		
IR_GAP	0.4345***	0.8061***		0.2299***		
	(0.0002)	(0.0004)		(0.0015)		
IMR					**-0.1205*** **	
					(0.0018)	
CCR						**-0.7664*** **
						(0.0033)
Intercept	-4.1368***	-7.6811***	-0.6281***	-2.5891***	-0.2731***	-0.5467***
	(0.0047)	(0.0084)	(0.0118)	(0.0302)	(0.0119)	(0.0117)

Obs	101,619,855	101,619,855	86,881,042	86,881,042	86,881,042	86,881,042
Prepayment rate/ Default rate	14.50%	14.50%	1.19%	1.19%	1.19%	1.19%
R-squared	9.60%	9.59%	17.64%	17.64%	17.75%	18.16%
AUROC	69.40%	69.40%	85.70%	85.40%	85.70%	86.00%

Note: Standard deviations are clustered by state and presented in parentheses * p =0.1, ** p = 0.5, *** p = 0.01.

For prepayment regressions, PP_PROBIT and PP_MNL show the parameter estimates for the first stage of a two-stage model (Stage 1) and a multinomial Logit model respectively. All parameter estimates generally show the expected signs and are significant. For instance, the FICO score is positive and significant, implying that borrowers with better credit quality are more likely to prepay. LTV is negative and significant, suggesting that an LTV implies a lower likelihood to prepay. LTV_CHANGE is negative and significant, suggesting that LTV increases result in lower prepayment risk as borrowers may have to pay a premium making refinance less attractive. LENDING_STD is negative and significant, implying tighter lending standards lead to lower prepayment probabilities. IR_GAP is positive and significant, implying that larger interest rate gaps result in higher interest savings for borrowers for refinance.

For default regressions, PD_Probit, PD_MNL, PD_IMR and PD_CCR are the estimated PDs for a Probit model, a multinomial Logit model, a two-stage model using correction term of IMR and a two-stage model using correction term of CCR. The parameter estimates for the default equation have generally the opposite signs to the prepayment equations across models. In particular, the FICO estimates are negative and significant, implying a borrower with better credit quality is less likely to default. The estimates of DTI and LTV are positive and significant, which is expected. The PD_MNL model requires the same covariates for both prepayments and defaults equations. To make a two-stage model valid (PD_IMR or PD_CCR), there is a need to have at least one variable in the prepayment equation different from the default equation (exclusion criteria). This is satisfied as we exclude LENDING_STD and IR_GAP from the default equations for PD_Probit and hence PD_IMR and PD_CCR. These are predictors for prepayments from supply and demand of refinance and only indirectly affect defaults through prepayments which is modeled in the second stage PD models. We confirm robustness for the choice of observed factors.

The parameter estimates of IMR and CCR in the two-stage models using different correction terms are negative and significant. This implies that there is a negative correlation of unobservable factors between prepayments and defaults, which is the evidence of the selection effect. CCR is estimated at -0.77.

There are different validation methods: discrimination, calibration and stability. R^2 is not an appropriate performance measure for binary variables such as payoff or default. Please note that discrimination measured by AUROC may not be comparable across different samples. Calibration measured by mean absolute errors (MAE) is a more comprehensive metric to assess how well a model provides an accurate prediction of risk levels. Also, MAE is aligned with other metrics like bank earnings, spreads, etc. This is why we focus on calibration performance.

We plot the relation between prepayments and defaults for pooled data in Figure 3.5. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes. The relation between default and prepayment risk follows a u-shaped pattern, suggested by our simulation study with high default rates for low and high prepayment risks. For example, the default rate is 2.7% for the bottom five percent and 2.2% for the top five percent of prepayment risks and less than 1% for medium prepayment risks. We compare the prediction quality of default events for four models in the later section.

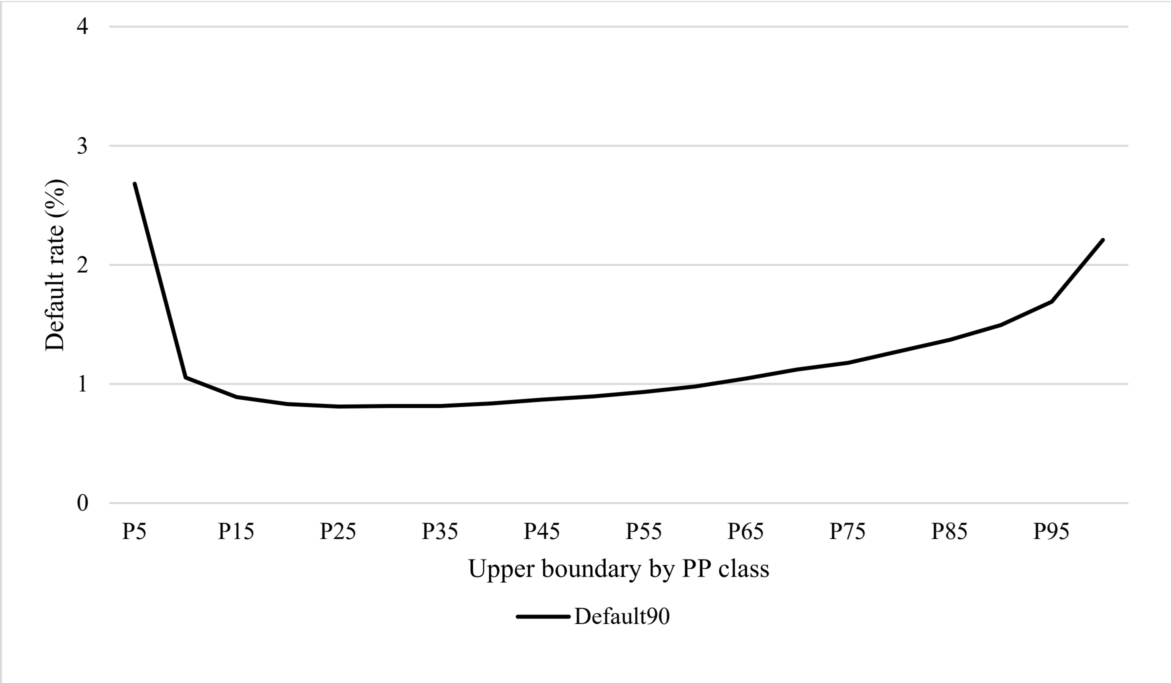


Figure 3.5. Relation between prepayment risk and default risk on pooled data

This figure shows the relation between prepayments and defaults for 20 classes for the observed sample post-prepayment for the pooled data. The averaged prepayment rate for the entire period is 14.5% and the averaged default rate is 1.2%. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

3.6.2.2 Economic upturns and downturns

We run models for two subsamples for economic upturns and downturns. We define the period from 2000 to 2006 as an economic upturn and the period from 2007 to 2009 as an economic downturn. Main regression results for prepayment and default models for economic upturns and downturns are in Table 3.5.

Table 3.5 Regression results on subsamples of upturns and downturns

This table reports the regression results for prepayment and default models for economic upturns and downturns. Panel A shows parameter estimates of two prepayment triggered variables, LENDING_STD and IR_GAP, in a Probit model (PP_PROBIT). Panel B shows the parameter estimates of the correction term in our model (PD_CCR).

	Upturns (2000-2006)	Downturns (2007-2009)
Panel A: Prepayment regressions		
LENDING_STD	-0.0789***	-0.0089***
	(0.0021)	(0.0007)
IR_GAP	0.9298***	0.1680***
	(0.0250)	(0.0242)
Borrower-specifics	Yes	Yes
Loan-specifics	Yes	Yes
Macroeconomics	Yes	Yes
Clustered by state	Yes	Yes
Obs	25,369,561	21,731,089
Prepayment rate	17.45%	10.61%
R-squared	25.94%	5.51%
AUROC	79.60%	65.50%
Panel B: Default regressions using CCR		
CCR	-0.6926***	-1.8381***
	(0.0322)	(0.2080)
Borrower-specifics	Yes	Yes
Loan-specifics	Yes	Yes
Macroeconomics	Yes	Yes
Clustered by state	Yes	Yes
Obs	20,943,452	19,425,508
Default rate	0.66%	1.72%
R-squared	19.91%	19.47%
AUROC	87.50%	85.50%

Note: Standard deviations are clustered by state and presented in parentheses * p =0.1, ** p = 0.5, *** p = 0.01.

Panel A shows parameter estimates of two variables triggering prepayments in Stage 1 of our model (PP_PROBIT). Prepayments are more responsive to lending standards and the gap in interest rates for economic upturns than for economic downturns. For instance, the estimate of LENDING_STD is -.0.08 for economic upturns and is -0.008 for economic downturns, which means lending standards have a higher impact on prepayments for economic upturns. Furthermore, the estimate of IR_GAP is 0.9 for economic upturns and is 0.2 for economic downturns, implying borrowers are more likely to refinance in economic upturns than in economic downturns.

Panel B shows the parameter estimates of correction term in our model (PD_CCR). The estimate of CCR for economic upturns is -0.69 and -1.83 for economic downturns. Both are negative and significant, suggesting negatively correlated unobservable factors and an existence of the selection effect. Note that the impact of this selection effect on default risk depends on prepayment probabilities as highlighted in Eq (19).

We plot the relation between prepayments and defaults for the upturns and downturns in Figure 3.6. The averaged default rate is 0.66% for economic upturns and 1.72% for economic downturns. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

For economic upturns, the default rate (dash black line) is the highest at 3.2% for the top five percent of prepayment risk. This implies that the remaining borrowers with a high prepayment risk are more likely to default.

For economic downturns, the default rate (the solid back line) exhibits an opposite pattern where the highest default rate of 6.6% belongs to the bottom five percent of prepayment risk. This suggests that high defaults are mainly explained by observed credit risk factors.

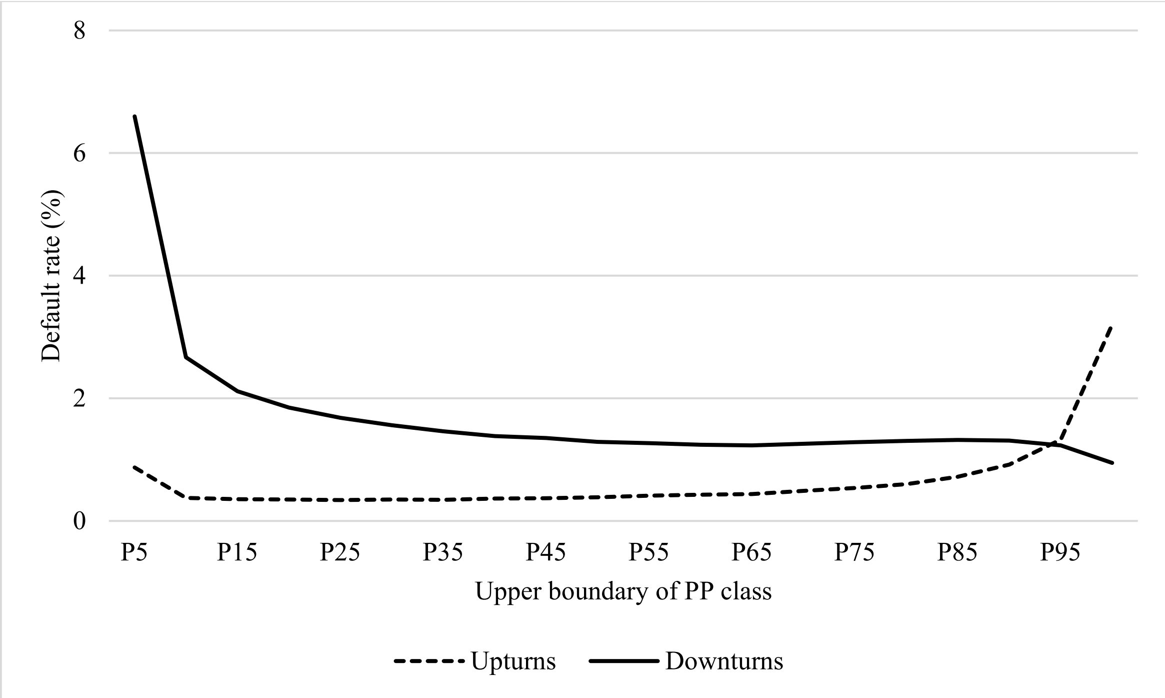


Figure 3.6. Relation between prepayment risk and default risk in upturns and downturns

This figure shows the relation between prepayments and defaults for 20 classes in our simulation study for the observed sample post-prepayment for economic upturns and downturns. The upturns are from 2000 to 2006 and the downturns are from 2007 to 2009. The mean of default rates is 0.66% and 1.72% respectively. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

3.6.2.3 LTV below and above 80% in economic upturns and downturns

So far, we have looked at the supply side through lending standings for economic upturns and downturns. In this section, we drill down into borrower-specific LTV ratios. We do not want to mix the effect of low/high LTV with macroeconomic states, thus we examine loans with LTV below and above 80% separately for economic upturns and downturns. We are able to do this analysis as we use zipcode level HPIs. We choose the threshold of 80% as it is a reasonably safe threshold that most lenders require borrowers to meet if there is no lenders' mortgage insurance. Prepayments are usually associated with low LTV below 80%. Specially, we observe that for economic upturns (downturns), the prepayment rate is 2% (2.8%) higher for loans with LTV below 80% than for loans with LTV above 80%. For default rates, for economic upturns loans with LTV below 80% is 0.5% lower than loans with LTV above 80% and for economic downturns this figure is 2.7% lower.

We run models for different LTV buckets for economic upturns and downturns. Most parameter estimates are similar to the regressions on the pooled data. The regression results for prepayment and default models for economic upturns and downturns are presented in Table 3.6.

Table 3.6 Regression results on subsamples with LTV below and above 80%

This table reports the regression results for prepayment and default models for loans with LTV below and above 80% stratified by economic upturns and economic downturns. Panel A shows the parameter estimates of two prepayment triggered variables in a Probit model (PP_PROBIT). Panel B shows the parameter estimates of correction term in our model (PD_CCR).

	Upturns (2000-2006)		Downturns (2007-2009)	
	LTV<=80	LTV>80	LTV<=80	LTV>80
Panel A: Prepayment regressions				
LENDING_STD	-0.0818***	-0.0673***	-0.0096***	-0.0079***
	(0.0024)	(0.0015)	(0.0007)	(0.0008)
IR_GAP	0.9443***	0.8626***	0.1741***	0.1690***
	(0.0262)	(0.0171)	(0.0250)	(0.0287)
Borrower-specifics	Yes	Yes	Yes	Yes
Loan-specifics	Yes	Yes	Yes	Yes
Macroeconomics	Yes	Yes	Yes	Yes
Clustered by state	Yes	Yes	Yes	Yes
Obs	20,766,160	4,603,401	15,472,656	6,258,433
Prepayment rate	17.81%	15.82%	11.41%	8.62%
R-squared	26.30%	25.06%	4.84%	7.36%
AUROC	79.70%	79.70%	64.30%	69.00%
Panel B: Default regressions using CCR				
CCR	-0.6700***	-0.7799***	-2.1185***	-0.9166**
	(0.0352)	(0.0288)	(0.0933)	(0.3396)
Borrower-specifics	Yes	Yes	Yes	Yes
Loan-specifics	Yes	Yes	Yes	Yes
Macroeconomics	Yes	Yes	Yes	Yes
Clustered by state	Yes	Yes	Yes	Yes
Obs	17,068,271	3,875,181	13,706,763	5,718,745
Default rate	0.57%	1.04%	0.92%	3.63%
R-squared	19.64%	19.56%	14.91%	16.68%
AUROC	87.60%	86.30%	83.80%	81.20%

Note: Standard deviations are clustered by state and presented in parentheses * p =0.1, ** p = 0.5, *** p = 0.01.

Panel A shows parameter estimates for LENDING_STD and IR_GAP triggering prepayments in Stage 1 of our model (PP_PROBIT). In both upturns and downturns, loans with LTV below 80% are more responsive to lending standards and the gap in interest rates. For instance, for economic upturns the estimate of IR_GAP for loans with LTV below 80% is 0.94, which is higher than the estimate of 0.86 for loans with LTV above 80%. Similarly, we also see greater impacts of lending standards for LTV below 80%.

Panel B shows the parameter estimates of correction term in our model (PD_CCR). The estimates of CCR are negative and significant for both LTVs below 80% and LTVs above 80%, indicating negatively correlated unobservable factors and an existence of the selection effect. In particular, for economic upturns, the estimates of CCR are -0.67 and -0.78 respectively for LTV below and above 80%. For economic downturns, the estimates of CCR are -2.12 and -0.92 respectively for LTV below and above 80%. The impact of this selection effect however, depends on prepayment probabilities.

We plot the relation between prepayments and defaults for LTV below and above 80% in Figure 3.7. The dash line represents the default rate for loans with LTV below 80%. The solid line represents the default rate for those with LTV above 80%. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

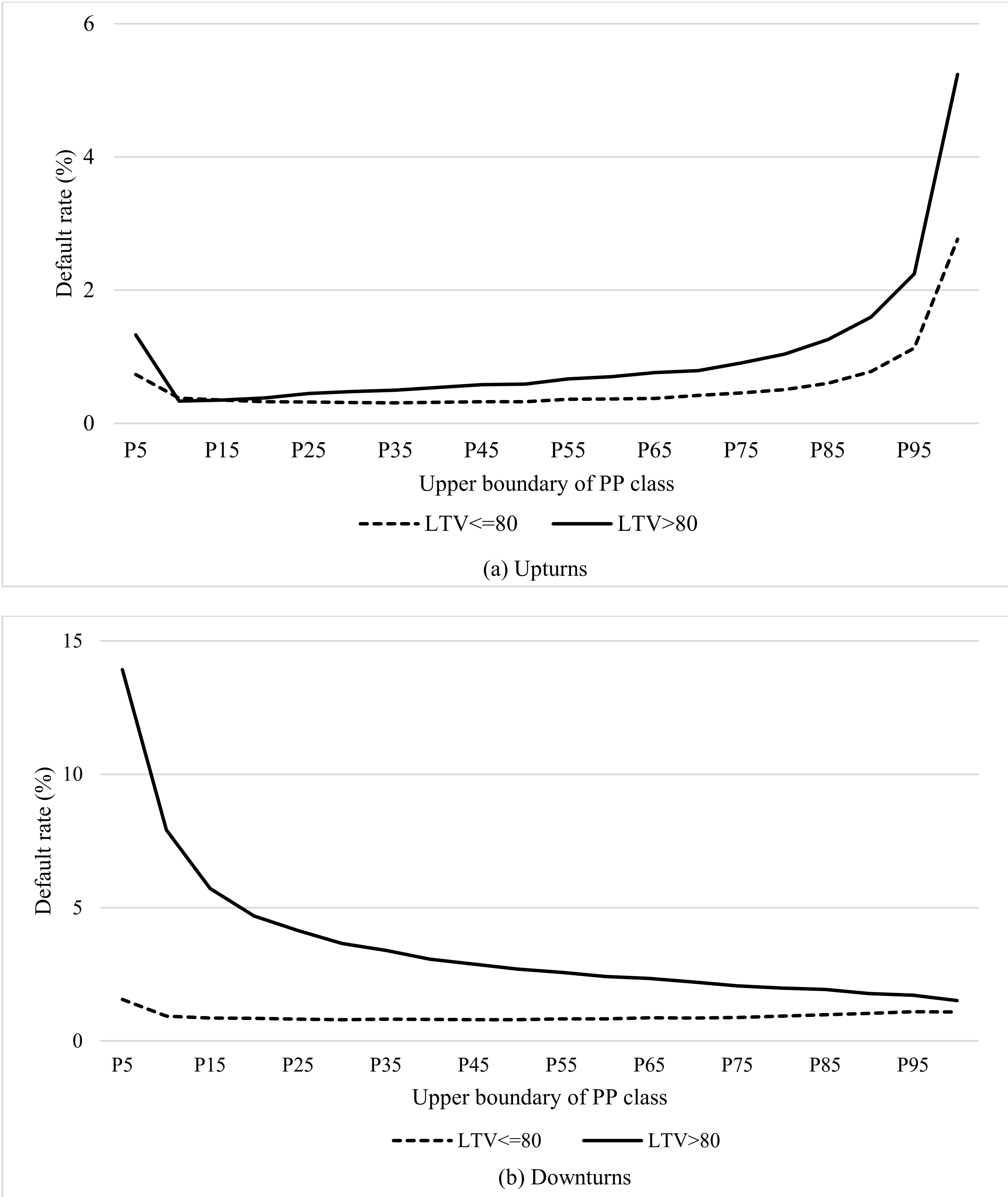


Figure 3.7. Relation between prepayment risk and default risk by LTV levels

This figure shows the relation between prepayments and defaults for 20 classes in our simulation study for the observed sample post-prepayment for loans with LTV below and over 80%. Figure 7a shows the default pattern for economic upturns from 2000 to 2006. Figure 7b shows the default pattern for economic downturns from 2007 to 2009. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. The x-axis labels P. are the percentile ranks of the upper boundaries of the PP classes.

Figure 3.7a shows the default pattern for economic upturns from 2000 to 2006. The default rate increases as prepayment risk increases, as a result of the selection effect. The highest default rate belongs to the 5% highest prepayment probabilities. Loans with LTV above 80% may be affected by the selection effect more than loans with LTV below 80%, resulting in a higher default rate at the 5% highest prepayment probabilities.

Figure 3.7b shows the default pattern for economic downturns from 2007 to 2009. The default rates for loans with LTV below 80% are similar across PP classes. For loans with LTV above 80%, the default rate decreases as prepayment risk increases, implying the dominance of the unconditional effect by observed factors. The highest default rate is around 14% at the tail of the bottom P5 of the lowest prepayment probabilities.

3.6.2.4 PDs calibration and accuracy of models

First, we report the calibration performance for predicted PDs by prepayment risk levels using the pooled data from 2000 to 2016 in Table 3.7.

We divide the observed post-prepayment sample into 20 PP classes. PP classes are defined as 5% intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. PD_Probit, PD_MNL, PD_IMR and PD_CCR are deviations of the mean of predicted PDs to default rate in each PP class.

The deviation is calculated as the difference between the mean of predicted PDs and the default rate divided by the default rate. A positive deviation means an overestimation of the default rate. A negative deviation means an underestimation of the default rate.

Table 3.7 Model calibrations for predicted PDs by prepayment risk levels

This table reports the calibration performance for predicted PDs by prepayment risk levels using the pooled data from 2000 to 2016. PP classes are defined as five-percent intervals with regard the percentile rank of the mean of PP_PROBIT and PP_MNL. Mean of PPs are the average of PP_PROBIT and PD_MNL in each PP class. PD_Probit, PD_MNL, PD_IMR and PD_CCR are deviations of the mean of predicted PDs from a Probit model, a multinomial Logit model, a two-stage model using IMR correction term and a two-stage model using CCR correction term respectively in each PP class.

PP class	Mean of PPs	Deviation of the mean of predicted PDs to default rate			
		PD_Probit	PD_MNL	PD_IMR	PD_CCR
P5	3%	16%	-14%	1%	-4%
P10	5%	31%	18%	24%	10%
P15	6%	31%	21%	25%	11%
P20	7%	29%	22%	24%	11%
P25	8%	25%	21%	21%	9%
P30	8%	21%	18%	18%	7%
P35	9%	18%	17%	17%	6%
P40	10%	14%	14%	13%	3%
P45	11%	9%	12%	10%	1%
P50	11%	7%	11%	8%	1%
P55	12%	3%	7%	4%	-1%
P60	13%	0%	6%	2%	-2%
P65	14%	-4%	3%	-1%	-3%
P70	16%	-9%	0%	-5%	-6%
P75	17%	-11%	-1%	-6%	-4%
P80	18%	-15%	-4%	-9%	-6%
P85	20%	-19%	-6%	-13%	-7%
P90	23%	-23%	-8%	-16%	-6%
P95	26%	-29%	-11%	-20%	-6%
P100	35%	-37%	-13%	-27%	2%

Prepayment risk increases across PP classes with the lowest PP of 3% for the lowest 5% of prepayment probabilities and 35% for the highest 5% of prepayment probabilities. Predicted PDs by all models overestimate defaults for low-prepayment-risk borrowers and underestimate defaults for high-prepayment-risk ones. The industry model (PD_Probit) is the worst at calibrating predicted PDs to default rate with the largest deviations on both sides. Specifically, for the bottom half of the lowest prepayment risk PD_Probit overestimates the default rate by 21% and for the top half of the highest prepayment risk PD_Probit underestimates default rate by 17%. The literature models (PD_MNL and PD_IMR) are slightly better than the industry model. Our two-stage model with the CCR correction term is the best at calibrating PDs to observed default rates. PD_CCR reduces the overestimation of the default rate only by 4% for the bottom half and the underestimation of the default rate by 3% for the top half. We also test the accuracy of models in a robustness check, if the sample is divided into less or more than 20 PP classes with consistent results.

To compare the overall accuracy across models, periods and LTV buckets, we use the mean absolute errors (MAE). The MAE is measured as the mean of absolute values of deviations across all PP classes. The comparison of MAEs for models is shown in Table 3.8.

Table 3.8 Accuracy of in-sample predicted PD across models

This table reports the mean absolute error (MAE) and the mean of positive/negative deviations post-prepayment in upturns and downturns. The deviation is measured as a difference between the mean of predicted PDs and the default rate divided by the default rate in each PP class. The MAE is measured as the mean of absolute values of deviations across all PP classes.

	Pooled data	Upturns			Downturns		
		LTV<=80	LTV>80	All	LTV<=80	LTV>80	All
Panel A: MAE across 20 PP classes							
PD_Probit	18%	34%	48%	37%	22%	7%	14%
PD_MNL	11%	16%	33%	19%	14%	7%	6%
PD_IMR	13%	25%	51%	32%	16%	4%	9%
PD_CCR	5%	6%	15%	8%	8%	3%	3%
Panel B: Mean of positive deviations							
PD_Probit	19%	36%	56%	39%	20%	3%	10%
PD_MNL	14%	15%	34%	18%	12%	7%	5%
PD_IMR	15%	27%	60%	36%	14%	3%	6%
PD_CCR	7%	7%	24%	10%	7%	2%	1%
Panel C: Mean of negative deviations							
PD_Probit	-17%	-26%	-25%	-27%	-25%	-10%	-19%
PD_MNL	-7%	-24%	-30%	-28%	-18%	-7%	-6%
PD_IMR	-12%	-19%	-26%	-18%	-20%	-5%	-14%
PD_CCR	-4%	-4%	-6%	-5%	-11%	-4%	-5%

Panel A reports the MAE across 20 PP class for four models. For pooled data, the highest MAE is 18%, which belongs to PD_Probit. The MAE of the industry model is higher at 37% for economic upturns and lower at 14% for economic downturns, implying that the industry model poorly captures the selection effect which dominates during economic upturns. For economic upturns, the MAE for loans with LTV above 80% is higher than for loans with LTV below 80%, suggesting a higher selection effect for LTV above 80%. The MAE for loans with LTV above 80% is considerably lower than for LTV below 80% for economic downturns. The literature model using IMR (PD_IMR) is better, followed by a competing risk model (PD_MNL). Our model, using the new correction term, provides the lowest MAE (8% for economic upturns and 3% for economic downturns) and hence dominates in predicting defaults.

Panel B reports the mean of positive deviations at PP classes that a particular model overestimates the default rate. Again, PD_Probit performs the worst and PD_CCR the best.

Panel C reports the mean of negative deviations at PP classes that a particular model underestimates the default rate. This side of miscalibration may result in a lower loan loss provisioning and bank capital, which is critical for bank risk management. The industry model (PD_Probit) can underestimate the PDs by 27% for economic upturns and 19% for economic downturns. The two-stage CCR model (PD_CCR) can reduce the underestimation to only 5% for both periods.

3.6.2.5 Out-of-sample forecasts

We perform an out-of-sample forecast in this section. We randomly divide the pooled data into two equally sized exclusive parts: a training and a validation sample. We obtain two comparable samples with the similar prepayment rates and default rates. Next, we estimate the models on the training sample, use the parameter estimates received to forecast PDs for the validation sample. Finally, we calculate the MAE for the four models for the validation sample, in order to assess the accuracy of the out-of-sample forecast.

We look into the out-of-sample forecast for primary purchase loans and refinancing loans. Primary purchase loans are for first time house owners and refinancing loans are for those who have already refinanced their loans at least once. There is a slight difference in default rates of these loan types. The averaged default rate for purchase loans is 1.15% and 1.21% for refinancing loans. The accuracy of models for in-sample estimation and out-of-sample forecasts is in Table 3.9.

Table 3.9 Accuracy of out-of-sample PD forecasts across models

This table reports the results for out-of-sample forecasts. Panel A reports the default rate and mean of predicted PDs for in-sample and out-of-sample forecasts. In-sample numbers are based on a 50% random sample of the pooled data. In-sample models are used to forecast for the remaining 50% of pooled data. The MAE is across all PP classes is a measure for overall accuracy of a model. Panel B shows the out-of-sample forecast for purchase and refinancing loans. Panel C shows discrimination measured by AUROC.

	Default rate	PD_Probit	PD_MNL	PD_IMR	PD_CR
Panel A: Out of sample					
In-sample (50% of data)	1.19%	1.17%	1.21%	1.18%	1.19%
Out-of-sample (the rest 50% of data)	1.19%	1.18%	1.21%	1.18%	1.19%
MAE for in-sample		18.00%	11.00%	13.00%	5.00%
MAE for out-of-sample		18%	11%	13%	5%
Panel B: Out of sample by loan type					
In-sample (50% of data)	1.19%	1.17%	1.21%	1.18%	1.19%
Out-of-sample (purchase loans)	1.15%	1.14%	1.17%	1.15%	1.16%
Out-of-sample (refinancing loans)	1.21%	1.19%	1.23%	1.20%	1.20%
MAE for out-of-sample (purchase loans)		16%	11%	12%	4%
MAE for out-of-sample (refinancing loans)		19%	12%	14%	6%
Panel C: Discrimination by AUROC					
In-sample data		86.12%	85.71%	86.13%	86.23%
Out-of-sample data		86.10%	85.81%	86.11%	86.20%

Panel A reports the default rate and mean of predicted PDs for in-sample and out-of-sample forecasts. In-sample is taken randomly by 50% of the pooled data, then models on in-sample are used to forecast for the remaining 50% of pooled data. The MAE is across all PP classes as a measure for overall accuracy of a model. As we have two comparable samples, the models in the training sample predict well for the validation sample. Across PP classes, PD_CCR provides the best calibration.

Panel B reports the default rate and mean of predicted PDs for out-of-sample forecasts for primary loans and refinancing loans. In-sample is taken randomly by 50% of the pooled data, the same as in Panel A. The out-of-sample forecasts are made separately for purchase loans and refinancing loans. PD_CCR is still the best model in calibrating PDs to default rates.

3.6.2.6 Robustness checks

Our first robustness check analyzes the accuracy of models for different numbers of PP classes. In the main tests, we divide the observed post-prepayment sample into 20 PP classes. There may be a concern about the aggregation of a larger number of loans into classes. To assess the consistency, we use results from regression models on the pooled data and re-bucket the prepayment probabilities into ten PP classes (deciles) and 50 PP classes. The greater the number of classes, the greater the calibration accuracy of models.

Our second robustness check is about using alternative default proxies. In the main tests, we use DEFAULT90 that takes the value of one if a loan is 90+ days overdue or in foreclosure. In this section, we use two alternative default proxies, DEFAULT60 and DEFAULT180, that take the value of one if a loan is 60+/180+ days overdue or in foreclosure. The parameter estimates are similar to the main tests.

Our third robustness check is an assessment of the model performance in relation to the observed factors included in the models. We run regressions for the pooled data using only four variables of FICO, DTI, LTV and LTV_CHANGE. We choose these variables as these are the most common factors the credit risk literature. In addition, we continue to include LENDING_STD and IR_GAP as prepayment triggered variables. We want to test the effect of biases in case control variables are limited, leaving a greater factor variation to the error terms.

The parameter estimates for four variables are similar to the main test. Regression results using a reduced number of observed factors also suggest negative correlations of unobservable factors between prepayments and defaults. We document that the default patterns are similar to the main test.[21] Table 3.10 consolidates the results on the accuracy of models for the three robustness checks.

[21] Results are available on request.

Table 3.10 Robustness check: accuracy of predicted PD across models

This table shows the robustness checks for accuracy of models. Baseline is the results from the main test on pooled data using 20 PP classes, the default indicator DEFAULT90 and the full set of risk factors. Robustness check 1 shows the accuracy of models on the pooled data if the observed sample post-prepayment is divided into different numbers of PP classes. Robustness check 2 shows the accuracy of models using alternative definitions of defaults. Robustness check 3 shows the accuracy of models on the pooled data with a reduced number of observed factors that are FICO, DTI, LTV and LTV_CHANGE. Variables are used to trigger the prepayment selection are still LENDING_STD and IR_GAP.

		Robustness check 1		Robustness check 2		Robustness check 3
	Baseline	10 PP classes	50 PP classes	DEFAULT60	DEFAULT180	Reduced risk factors
Panel A: Mean absolute error across all PP classes						
PD_Probit	18%	18%	18%	17%	23%	46%
PD_MNL	11%	10%	12%	5%	22%	24%
PD_IMR	13%	13%	14%	7%	25%	25%
PD_CCR	5%	4%	6%	4%	13%	18%
Panel B: Mean of positive deviations						
PD_Probit	19%	18%	19%	17%	26%	55%
PD_MNL	14%	12%	14%	6%	26%	34%
PD_IMR	15%	14%	16%	7%	28%	30%
PD_CCR	7%	5%	7%	6%	16%	24%
Panel C: Mean of negative deviations						
PD_Probit	-17%	-17%	-17%	-16%	-19%	-32%
PD_MNL	-7%	-7%	-8%	-4%	-16%	-13%
PD_IMR	-12%	-12%	-12%	-7%	-22%	-16%
PD_CCR	-4%	-3%	-4%	-3%	-9%	-12%

The baseline results for the main test using pooled data are based on 20 PP classes, default indicator DEFAULT90 and a full set of risk factors.

Robustness check 1 shows the accuracy of models on the pooled data if the observed sample post-prepayment is divided into different numbers of PP classes. The MAE of PD_Probit is consistent at 18% even when the number of PP classes changes. The MAEs of PD_MNL, PD_IMR and PD_CCR fluctuate by 1% or 2% for different numbers of PP classes. The mean of positive/negative deviations does not vary much if using different numbers of PP classes. This evidence suggests that our findings are robust.

Robustness check 2 shows the accuracy of models using alternative default proxies. The highest MAE belongs to PD_Probit, followed by PD_IMR. The competing risks model, PD_MNL is good. Our model PD_CCR performs the best with the lowest MAE. This evidence suggests that our findings are robust.

Robustness check 3 shows the accuracy of models using four observed factors that are FICO, DTI, LTV and LTV_CHANGE. The highest MAE is 46% for PD_Probit. The lowest MAE belongs to our model (PD_CCR) at 18%. Compared to using a full set of risk factors, the MAE is higher across all models when reducing risk factors included in the models. This evidence suggests that our findings are robust.

We obtain similar findings for the sub-sample models, i.e., different macroeconomic periods (upturns and downturns) and LTV buckets.[22]

[22] Results are available on request.

3.7 Conclusions

Our study investigates the impact of mortgage prepayments as a selection mechanism on defaults. Firstly, we use a simulation study to decompose the relation between prepayments and defaults into two effects: an unconditional effect by observed common factors and a selection effect by correlated unobservable factors. In an empirical study, we find that high defaults are likely to occur for two distinct groups. The first group includes borrowers who have low-prepayment-risk as suggested by observed factors (unconditional effect). The second group includes borrowers who have high-prepayment-risk, but did not refinance and remain in the sample post-prepayment (selection effect). The selection effect may be driven by omitted information that is recognized by other lenders in the refinance process (i.e., soft information).

Secondly, we find that the main cause for high defaults for economic upturns is different from economic downturns. For economic upturns, the selection effect dominates, indicating a higher default risk for high-prepayment-risk borrowers. For economic downturns, the unconditional effect is the key to explaining high default rates. Understanding default patterns in different states of the business cycle can help to predict PDs more accurately.

Lastly, we find that using a common industry model (e.g., a Probit model) leads to a significant error in PD calibration. This error is visible when calibration is analyzed by prepayment levels. Specifically, for the group of borrowers who have relatively high-prepayment-risk but do not prepay, Probit models may underestimate default risk. We observe that literature models controlling for prepayments (a competing risk model and a two-stage model using a correction term of IMR) are slightly better than the industry model. We propose a two-stage model with a new correction term and find that our technique outperforms both the industry model and literature models by reducing MAEs from 18% to 5%.

Our study leads several policy implications for prudential regulators. Regulators should be aware of the impact of prepayments on default risk of mortgage portfolios. Omitting this selection effect may result in inadequate loan loss provisioning or capital requirements for high-prepayment-risk segments, especially during economic upturns. This error is measurable when calibration is analyzed by prepayment levels.

For banks controlling for prepayment behavior, it is important to assess both prepayment and default risks for loan pricing to remain competitive. Low default risk borrowers will receive a better price and stay, while high default risk borrowers (‘lemons’) will move to competitors with less accurate models.

Our analysis may further provide new insights into other selection areas, such as the removal of delisted companies and customer churn, on which the literature is equally sparse.

Chapter 4: Multi-Period Forecasts of Mortgage Credit Risk in the Presence of Prepayment Selection

4.1 Abstract

This paper explores two approaches to estimating prepayment risk and default risk in the multi-period setting: a life-cycle model and a forward model. Using data of US fixed-rate prime mortgages from 2000–2016, we find that both models perform equally well for prepayment and default predictions in the first three years, while the accuracy of both models decreases for longer periods. A life-cycle model provides a better calibration for later ages, while a forward model is more accurate in forecasts for longer times. We analyze the impact of prepayment selection on multi-period default predictions. We find default model, which controls for prepayment selection, provides more accurate default probabilities in long run than without selection. The mean absolute error of model with prepayment selection can reduce by nearly 50% compared to the model without selection. Our findings are useful for banks to more accurately assess mortgage risk over the loan lifetime and implement loan loss provisioning changes under international accounting standards.

4.2 Introduction

4.2.1 Motivation

Mortgage is a long-term financial product with a general tenor of 30 years. Credit risk associated with mortgage includes prepayment risk and default risk. Either event can occur at any point during the loan's lifetime. The longer the term of mortgages, the higher the uncertainty of both borrower risk and macroeconomy, and, thus, the harder for banks to predict credit risk. The literature has provided numerous applications to predict default in the next period, but there are few applications for predicting mortgage risk beyond one period.

Recent revisions of the bank regulations, including IFRS 9 and US GAAP, require an estimation of the expected credit loss over the lifetime of a mortgage. The lifetime may be of time to prepayment, time to default, or time to maturity. Understanding mortgage decisions over its lifetime is important to enabling accurate multi-period forecasts.

The literature has proposed three main approaches for estimating PD in the multi-period setting. The first approach is survival analysis,[23] namely, the parametric AFT model and the semiparametric CPH model. The AFT model strictly assumes a specific distribution of the survival time, while the CPH model allows for baseline hazard varying across time but relies on an assumption about a proportional hazard across individuals. Therefore, such models lose their capability to capture flexible changes over the lifetime of mortgages.

The second approach is the splines based discrete time survival model. This approach uses Probit/Logit regressions and incorporates a function of age for the dynamic future forecasts.[24] In comparing methods of survival analysis, Banasik, Crook and Thomas (1999) find that those methods are competitive in default forecast in the first year. Luo, Kong, and Nie (2016) find the splines based discrete time survival model can improve prediction accuracy. Most studies apply this method for forecasting risk on credit cards. Applications for risks on mortgages are limited. When using age, mortgages reflect consumer life cycles more accurately than any other form of consumer loans. This is strongly supported by the household life-cycle theory (Morrow-Jones and Wenning, 2005; Clapp et al., 2001). Borrower age and lifecycles are closely related. Consumer life stages include birth, education, marriage and divorce, children,

[23] Survival analysis has been applied for the asset classes of personal loans (Stepanova and Thomas, 2002; Tong, Mues, and Thomas., 2012), credit cards (Gross and Souleles, 2002; Bellotti and Crook, 2009), and corporate bonds (Krüger et al., 2018).
[24] Extensive work using a discrete time survival model has been conducted on credit cards (e.g., Bellotti and Crook, 2013; Luo,Kong and Nie, 2016; Djeundje and Crook, 2019).

retirement, disabilities and death. Borrower age is sometimes not observed and sometimes not considered as age, gender and race are sensitive borrower characteristics. Often borrower age is related to loan age as the age of borrowers at loan origination is distributed around a certain age. For example, many mortgage borrowers will be approximately 30 years old when taking out their first mortgage. Loan age is also important to reflect time-varying contractual features such as the loan amortization schedule. This approach to mortgages is hereafter called a life-cycle model in this study.

The third approach is a forward model that uses only known information to predict probabilities in different horizons. This approach is usually only used in corporate default.[25] Studies using a forward model focus on the predictability of factors such as distance-to-default, net income ratio, cash ratio, market-to-book ratio, and volatility to corporate default for multi-period ahead. There are two main distinctions between corporate finance and household finance. First, companies do not have a specific life cycle like consumers. Corporates are linked to products. Product life stages include development, introduction, growth, maturity, and decline. Corporates often own multiple products at different life stages benefiting from portfolio diversification. Second, the risk factors in mortgages are very different to those used in corporate.

This study makes two contributions to the literature. First, it compares the adaptability of the life-cycle modelling approach and forward modelling approach in mortgages. Each method has different features and are based on different theories.[26] We find that both models perform well for prepayment and default predictions in the first three years, while the accuracy of both models decreases for longer periods. We find that a life-cycle model provides a better calibration for later ages, while a forward model is more accurate in forecasts for longer times.

[25] See, for example, Duan et al. (2018), Orth (2013), Duan, Sun and Wang (2012), and Campbell, Hilscher and Szilagyi (2008).
[26] Differences in model features are shown in Table 4.1.

Second, we control for prepayment selection for multi-period default forecasts. Default is a conditional process on prepayment. A borrower defaults at any point when they have not paid off their loan in all previous periods. We employ a two-stage model to control for prepayment selection. A credit correction ratio (CCR) derived from the first stage of prepayment regression is included in the second stage of default regression. We compare the default risk for multi-period forecasts between models with and without controlling for prepayment selection. We find that a model with selection provides better predictions in both the short and long run. A model without selection will overestimate default risk for any period over three years ahead.

4.2.2 Research approach

We first estimate life-cycle models for prepayment and default using a sample of US fixed-rate prime mortgages from 2000–2016. We employ independent and dependent models. Independent models are two independent regressions for prepayment and default. Dependent models include the first stage of prepayment regression and second stage of default regression controlling for prepayment selection. For both versions we use loan age as a proxy of changes over the life cycle and fit the prepayment rate and default rate across ages. We test different functions of age and choose the form that provides the best fit with the empirical data. Outcomes of the model are marginal probabilities at a certain age. For multi-period forecasts, we compute the survival probability as a loan is only prepaid or defaulted on at a certain age if it has survived at all previous ages. We then calculate the conditional probabilities adjusted by survival probability. From regression results, we find that most risk factors explain for prepayment and default in opposite directions. We assess the in-sample discriminative accuracy[27] by measuring the area under receiver operating curve (AUROC). Given the selected factors, the

27 Discriminative accuracy is the ability to distinguish low-risk and high-risk borrowers.

discriminative accuracy of the prepayment model (71.4%) is lower than that of the default model (86.5%). We also report the in-sample calibration results over age.[28] For the default model, the model controlling for prepayment selection provides a better fit than without selection by reducing the mean absolute error (MAE)[29] from 19% to 12%.

Next, we estimate a forward model using lagged variables for one-year to ten-year forecasts. We employ independent and dependent models. Independent models are two independent regressions for prepayment and default. Dependent models include the first stage of prepayment regression and the second stage of default regression controlling for prepayment selection. We report parameter estimates in multiple forward models. We document that most risk factors show good predictive ability for prepayment and default for up to three years ahead. For longer periods, lagged covariates lose their significance or the rational sign. Among common risk factors, FICO score appears to the most consistent in its predictability for both the short and long run. The discriminative accuracy of forward models decreases over horizons. For prepayment, AUROC is the highest (at 71%) for the one-year model, but decreases significantly beyond one period to just over 60%. For the default model, AUROC is the highest (at 86.5%) for the one-year model, but decreases significantly beyond one period to around 60%. We also report the in-sample calibration results. Given the functions of age chosen, model fit over ages for prepayment is better than model fit for default with the lower MAE. Regarding default models, for predictions of up to three-years, the model controlling for prepayment provides a better fit than the model without selection. The longer future periods, there is a similar calibration accuracy.

28 Calibration accuracy is the ability to obtain the mean of probabilities equalling actual prepayment/default rates over ages or times.
29 We measure the deviation as the difference between the mean of predicted probabilities and the actual rate divided by the actual rate at a certain age/time. MAE is measured as the average of absolute deviations across all ages or times.

We perform the first test for multi-year forecasts by age to predict the prepayment/default probabilities of new loans for up to 10 years. For prepayment forecasts, we find that the life-cycle model outperforms the forward model. The MAE across ages is 14% and 50% respectively. Both models perform equally well for prepayment forecasts in the first three years, with both having the MAE of 6–7%. Calibration accuracy decreases as age increases. For default forecasts, the life-cycle model outperforms the forward model. In term of selection, default model controlling for prepayment selection performs better than without selection by reducing the MAE by nearly 50% (from 61% to 34%).

We perform a second test for multi-year forecasts by time that predicts prepayment/default probabilities for a portfolio consisting of multi-age loans. We look at the portfolio at a specific base time (e.g., year) to predict probabilities for up to 10 years ahead. We consider base times as every single year of 2000–2009 and roll over predictions for the next 10 years. For both prepayment and default forecasts, we find that the forward model provides a better calibration than the life-cycle model. For default forecasts, models controlling for selection always outperform models not controlling for selection. The life-cycle default model controlling for selection reduces the MAE from 36% for uncontrolled models to 25%. Forward models controlling for selection only slightly reduce the MAE of uncontrolled models by 1%.

Our findings have implications for industry practice in multi-period mortgage risk predictions. For new loans joining to the portfolio, banks only know information at origination. Hence, we recommend the method of the life-cycle model to predict mortgage risk for multi-year ahead. For existing older loans in the portfolio, information is updated to the latest period. Hence, we recommend the forward model for those loans in multi-period forecasts. For default risk, we find that models controlling for prepayment selection are superior to uncontrolled models in terms of calibration accuracy.

This study proceeds as follows. Section 4.3 reviews the literature, Section 4.4 describes our modelling approach, Section 4.5 analyzes the empirical data for US fixed-rate prime mortgages, Section 4.6 provides validation tests and robustness check, Section 4.7 summarizes the study's findings and the policy implications.

4.3 Literature review

4.3.1 Concepts of modelling term structures

A life-cycle model and a forward model have different features. Table 4.1 summarizes the key features of the two models for multi-period payment and default forecasts.

Table 4.1 Comparison of life-cycle model and forward model

This table summarizes the main features of the life-cycle and the forward model for multi-period prepayment /default forecasts.

	Life-cycle model	Forward model
Target risk measure	Prepayment/default at a certain age	Prepayment/default during a period
Assumption	Mortgage decisions are linked to consumer life cycles	Current information is predictive of future events in both the short and long term
Effect measured	Marginal effect	Marginal effect
Selection condition	Conditional on survival at previous age	Conditional on survival at previous time
Data type	Panel (point in time)	Panel (rolling over)
Covariates used	Most recent variables	Lagged variables
Parameter estimates	Each factor has one estimate (β)	Each factor has multiple estimates (β) for different horizons
Fitting data	By age	By future time
Information measurement	At the beginning of age	At the beginning of lagged period
Multi-period forecasts	Forecast time-varying factors (e.g., macro-variables)	Not required

In the life-cycle model, the intuition is that housing finance and consumer life cycles are intrinsically related. By that, age is often used as a proxy for changes in life. The target measure is a marginal effect of prepayment and default at a certain age. A life-cycle model is a conditional model as the prepayment/default at a certain age is only observed if a loan has not been prepaid or defaulted on in a previous age (selection bias). The model can be estimated on panel data using the most recent covariates. Each risk factor has one estimate (β) aiming to fit the data by age. A major benefit of this model is that age is certainly known for all future periods. However, for multi-period forecasts, there may be a need to forecast time-varying variables.

In the forward model, the intuition is that current information is predictive of future events for both short and long horizons. The model uses known data (lagged covariates) to predict marginal prepayment and default probabilities for subsequent multi-periods. A forward model is a conditional view as the prepayment/default at a forward time is only observed if the loan survives until then. Each factor has multiple estimates (β) for different horizons. Thus, a forward model can provide the distinguished effects of risk factors for different horizons. However, as the predictions are based on prior information, long horizon forecasts are increasingly inaccurate the further the predicted period from the current period. The literature on assessing credit risk using the two models is summarized in Table 4.2.

Table 4.2 Related literature using two approaches for multi-period forecasts

Panel A shows studies applying life-cycle modelling approach and Panel B shows studies using the forward modeling approach.

Study	Event	Data period	Asset class	Country
Panel A: Life-cycle models				
Djeundje and Crook (2019)	Default	2008–2011	Credit card	UK
Luo, Kong and Nie (2016)	Default	n/a	Credit card	n/a
Bellotti and Crook (2013)	Default	1999–2006	Credit card	UK
Gross and Souleles (2002)	Default	1995	Credit card	US
Athreya (2008)	Default	2001	Personal debt	US
Livshits, MacGee, and Tertilt (2007)	Default	1996–1997	Personal debt	US vs. Germany
Pennington-Cross and Chomsisengphet (2007)	Prepayment/default	1993–2003	Mortgage	US
Morrow-Jones and Wenning (2005)	Prepayment	1995–1996	Mortgage	US
Clapp et al. (2001)	Prepayment/default	1993–1998	Mortgage	US
Panel B: Forward models				
Duan et al. (2018)	Default	2000–2014	Corporate	Korea
Hwang and Chu (2014)	Default	1984–2011	Corporate	US
Orth (2013)	Default	1980–2010	Corporate	US
Duan, Sun and Wang (2012)	Default	1991–2011	Corporate	US
Campbell, Hilscher and Szilagyi (2008)	Default	1963–2003	Corporate	US

Note. UK = United Kingdom, US = United States.

4.3.2 Credit risk by life-cycle models

The literature has extensively explored the default pattern of credit card loans over time. Djeundje and Crook (2019) build a model with time-varying coefficients and compared it to a model with constant coefficients. Luo, Kong and Nie (2016) provide an extension on an attrition model to predict the likelihood that customers will pay off a balance and close their credit accounts. Both studies found that splines based survival models outperform standard survival models in default prediction. Bellotti and Crook (2013) find that PD peaks at eight months then slowly declines over time. Gross and Souleles (2002) show that PD follows a hump shape, increasing for two years after an account is opened and then declining.

Several studies provide insights into the bankruptcy decisions of consumers over the life cycle of personal loans. Livshits, MacGee and Tertilt (2007) find that the default rate is highest during the early stage of adulthood (around the age of 25) and declines afterwards. The reasons for this are income shocks and expense uncertainty over the life cycle. Athreya (2008) find that the default rate is high among young people, peaks at 30, and is low in later years.

The literature on the life cycle of mortgages starts by analyzing the consumer decision of owning a house. Mnasri (2015) find a low rate of home ownership among young consumers (20–29 years old) due to their high geographic mobility. Attanasio et al. (2012) find that consumers delay purchasing their first home when incomes are low or uncertain. Iacoviello and Pavan (2013) find that a lower required down payment leads to an increase in the home ownership rate because young consumers with small net worth can afford the down payment. Halket and Vasudev (2014) find that the home ownership rate for households is over 70%.

Over the life cycle of mortgages, prepayment can be triggered by residential mobility, which can be explained by the housing life cycle model. Quigley and Weinberg (1977) suggest that household size, composition, and housing preferences are correlated with different stages of nuclear family formation (marriage), expansion (birth of children), contraction (maturation of children), and dissolution (death of a spouse).

Morrow-Jones and Wenning (2005) show that age is a reasonable basis on which to predict the decisions of US homeowners to move up or down in house price over the household life cycle. The presence of children, divorced or separated householder, income, and survival of ownership provide a more complete formulation and are more useful for policymaking. Clapp et al. (2001) show that borrower age is negatively related to prepayment triggered by moving and less significant for refinancing for lower rates. Pennington-Cross and Chomsisengphet (2007) show that prepayment rate and default rate increase from loan origination for 1.5 years and then tend to level out and oscillate around a fixed rate.

Although the literature extensively documents mortgage decisions over the consumer life cycles, there is a scarcity of studies detailing applications for predicting mortgage risk over the life cycle. Given banks' constant facing of prepayment risk and default risk for mortgages, understanding how life-cycle effects help to predict mortgage risk is useful in credit risk management.

We extend the literature by constructing a life-cycle model for mortgages that can predict prepayment risk and default risk for multiple future periods. We use loan age as a proxy for changes over the mortgage lifetime. We hypothesize that prepayment and default have a tendency to occur at certain stages throughout a 30-year period due to certain occurrences in the consumer life cycle.

4.3.3 Credit risk by forward models

Campbell, Hilscher and Szilagyi (2008) pioneer the idea of a forward model. Their study employed a multiple Logit model using lagged variables in an attempt to predict corporate bankruptcy for different time horizons. Their aim was to assess the predictability value of several commonly used factors such as distance-to-default, net income ratio, cash ratio, market-to-book ratio, and volatility to default. However, their study did not assess the accuracy of, or validate, models over different horizons.

Duan, Sun and Wang (2012) develop a forward intensity default model using only known data to predict corporate default in multiple future periods. Their study showed that the model's prediction was very accurate for shorter horizons (i.e., less than a year), but that its accuracy deteriorates when the horizon is increased to two or three years. Nevertheless, its performance remains reasonable.

Several extensions were made in recent years following a similar method. Orth (2013) proposes an extension to incorporate time-varying covariates in multi-period predictions. Hwang and Chu (2014) propose replacing the binary response variable with multinomial responses, thereby allowing for firms exiting public markets for different causes. Duan et al.

(2018) extended the model on private firms and found a methodology to obtain a public-firm equivalent distance-to-default by projection that references the distance-to-defaults of public firms with comparable attributes.

Unlike the above studies, which all dealt with corporate default, we explore the adaptability of a forward model for mortgage risk. The risk factors in mortgages are quite much different from those used in corporate default, and we assess the predictability value of those risk factors for prepayment and default in multi-periods.

4.4 Modelling frameworks

4.4.1 Life-cycle modelling approach

In our life-cycle model, AGE is a variable indicating the number of years since origination of mortgages. We start each loan with an AGE of one. The terms P_{it} and D_{it} indicate whether mortgage i at time t is prepaid or defaulted on respectively. $Risk_{it,P}$ and $Risk_{it,D}$ are two vectors of risk factors for prepayment and default and are not necessarily the same. PP_{it} and PD_{it} are prepayment and default probabilities. We develop a two-stage statistical model for prepayments and defaults, with the model for the first stage (prepayment regression) being as follows:

Stage 1: Prepayment model

$$\begin{aligned} PP_{it} &= \Pr\left(P_{it} = 1 \middle| g(AGE_{it}), Risk_{it-1,P}\right) \\ &= \Phi(\alpha_P + \beta_P g(AGE_{it}) + \gamma_P Risk_{it-1,P}) \end{aligned} \quad (1)$$

In Eq (1), prepayment probability is a function of age ($g(AGE_{it})$) representing the prepayment pattern of the life cycle, and a vector of risk factors at time $t-1$ (the most recent information). A panel data is observed. Loans are included in every period if they are not prepaid and have not defaulted. The default indicator of prepaid loans is set to zero until the time they were prepaid with the default indicator. Hence, Eq (1) provides a marginal prepayment estimation at a particular age.

For a function of AGE, Bellotti and Crook (2013) used a set of $(t, t^2, logt,\ (logt)^2)$ as a proxy for the life cycle. Follow that, we choose $g(AGE_{it}) = AGE_{it} +\ AGE_{it}^2 + \ln AGE_{it} + (\ln AGE_{it})^2$. We find that the combination of a quadratic function of AGE and natural logarithm of AGE provides the best fit for our empirical data.[30] This approach is common in survival models, but can also be included in time-discrete hazard models including Probit models. For example, Luo, Kong, and Nie (2016) used a cube splines function, and Djeundje and Crook (2019) used a time function for coefficients of risk factors.

For $Risk_{it,P}$, we categorize the vector of risk factors into two types: metric risk factors and dummy controls. Metric risk factors include proxies for borrower credit profile, loan quantitative features, and macroeconomic factors. Dummy controls include borrower type, loan type, and locations of properties. We use a Probit function to estimate Eq (1), where $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution.

In the second study (Chapter 3), prepayment had a selection effect on default. After the first stage, we can calculate a CCR for the second stage (default regression) as:

$$CCR_{it} = \frac{-\phi(\hat{\alpha}_P + \hat{\beta}_P g(AGE_{it}) + \hat{\gamma}_P Risk_{it,P})}{1 - \Phi(\hat{\alpha}_P + \hat{\beta}_P g(AGE_{it}) + \hat{\gamma}_P Risk_{it,P})} \tag{2}$$

[30] We also tried other function forms, such as a quadratic function, cubic function, and the fourth degree of polynomials. However, the results were inconsistent with our empirical data.

CCR is the correction term for any correlated unobservable factors between prepayment and default. CCR measures omitted variables derived from the prepayment process. CCR is negative and is calculated as the probability of prepayment over the cumulative probability of non-prepayments, in which $\phi(.)$ is the density function and $\Phi(.)$ is the CDF of the standard normal distribution. We control for prepayment selection as follows:

Stage 2: Default model with controlling for prepayment selection

$$\begin{aligned} PD_{it} &= \Pr\left(D_{it} = 1 \middle| h(AGE_{it}), Risk_{it,D}, P_{it} = 0\right) \\ &= \Phi(\alpha_D + \beta_D h(AGE_{it}) + \gamma_D Risk_{it,D} + \theta CCR_{it}) \end{aligned} \tag{3}$$

In the Eq (3), default probability is a function of age $h(AGE_{it})$ representing the default pattern of the life cycle, a vector of risk factors at time $t-1$ (most recent information), and a non-prepayment at time t. As the panel data records active loans at any point in time and excludes loans prepaid or defaulted on in previous periods, Eq (3) provides a marginal default estimation.

For $h(AGE_{it})$, we use the fourth degree of polynomials function because it is the best function by which to simulate the empirical pattern of default rates in respect to age.[31] Hence, $h(AGE_{it}) = \sum_{k=1}^{4}(\beta_{k,P} AGE_{it}^{k})$. Note that $h(AGE_{it})$ is not necessarily the same as $g(AGE_{it})$ used in the prepayment model.

For $Risk_{it,\mathrm{D}}$, we categorize the vector of risk factors into two types: metric risk factors and dummy controls. Metric risk factors include proxies for borrower credit profile, loan quantitative features, and macroeconomic factors. Dummy controls include borrower type, loan type, and locations of properties.

[31] We also tried other function forms, such as a quadratic function, cubic function, the fourth degree of polynomials, and a mix of logarithm components. However, the results were inconsistent with our empirical data.

To control for prepayment selection at time t, we include the credit correct term time CCR in the default model. The parameter θ indicates the correlation of unobserved factors between prepayment and default at the same time t.

We used a Probit function to estimate Eq (3), where $\Phi(.)$ is the CDF of the standard normal distribution.

Note that we also run a version of default model without controlling for prepayment as a benchmark. The model is specified similarly to Eq (3) but without the credit correction ratio CCR.

$$PD_{it} = \Pr\left(D_{it} = 1 \middle| h(AGE_{it}), Risk_{it,D}\right)$$
$$= \Phi(\alpha_D + \beta_D h(AGE_{it}) + \gamma_D Risk_{it,D}) \tag{4}$$

In Eq (4), default probability is conditional on a function of age and risk factors. The credit correction term (CCR) is excluded from model. This specification is a model without selection or uncontrolled model.

4.4.2 Forward modelling approach

A forward model uses lagged variables to predict future event likelihood. At the end time t, we know the values of the prepayment and default indicators. However, we use the lagged control variables at time ($t-1, t-2, \ldots, t-\tau$), where τ is a future period, to predict those events. We employ a two-stage forward model:

Stage 1: Forward prepayment model

$$PP_{it} = \Pr\left(P_{it} = 1 \middle| g(AGE_{it}), Risk_{i(t-\tau),P}, \tau\right)$$
$$= \Phi\{\alpha_P(\tau) + \beta_P(\tau) g(AGE_{it}) + \gamma_P(\tau) Risk_{i(t-\tau),P}\} \tag{5}$$

In Eq (5), a τ-period forward prepayment probability is conditional on a function of age at the time of prepayment, a vector of risk factors observed in the past at time $(t-\tau)$. The panel data records active loans at any point in time and excludes loans prepaid or defaulted on in previous periods. Hence, Eq (5) provides a marginal prepayment estimation for τ-period ahead. The function of AGE, $g(AGE_{it})$, is the same as that in Eq (1).

The sets of intercepts ($\alpha_P(\tau)$), coefficients of the age function ($\beta_P(\tau)$), and coefficients of risk factors ($\gamma_P(\tau)$) vary across different horizons (τ). The covariate AGE_{it} is at the time of prepayment, and $Risk_{i(t-\tau),P}$, is taken from lagged variables by τ periods.

After Stage 1, we calculated the credit correction term from Eq (5) followed by a formula presented in Eq (2). The next step is to include CCR in the forward default models:

Stage 2: Forward default models with controlling for forward prepayment

$$\begin{aligned} PD_{it} = {} & \Pr\left(D_{it}=1 \middle| h(AGE_{it}), Risk_{i(t-\tau),D}, PP_i = 0, \tau\right) \\ & = \Phi\{\alpha_D(\tau) + \beta_D(\tau)h(AGE_{it}) + \gamma_D(\tau)Risk_{i(t-\tau),D} + \theta(\tau)CCR_{it}\} \quad (6) \end{aligned}$$

In Eq (6), a τ-period forward default probability is conditional on a function of age at the time of default, a vector of risk factors observed in the past at time $(t-\tau)$, and prepayment at time t. The panel data records active loans at any point of time and excludes loans prepaid or defaulted on in previous periods. Thus, Eq (6) provides a marginal default estimation for τ-period ahead. We use the same function of $h(AGE_{it})$ as in Eq (3).

The sets of intercepts ($\alpha_D(\tau)$), coefficients of the age function ($\beta_D(\tau)$), and coefficients of risk factors ($\gamma_D(\tau)$) vary across different horizons (τ). The covariate AGE_{it} is at the time of default, and $Risk_{i(t-\tau),D}$ is taken from lagged variables by τ periods.

The coefficients of CCR, $\theta(\tau)$, can be interpreted as the correction bias of the forward prepayment at horizon τ for the forward default at the same horizon, τ.

In a special case of $\tau = 1$, the one-period forward model is identical to the life-cycle model as both use the most recent data to predict prepayment and default.

Note that we also run a version of default model without controlling for prepayment as a benchmark. The model is specified similarly to Eq (6) but without the credit correction ratio CCR.

$$\begin{aligned} PD_{it} = \; & \Pr\left(D_{it} = 1 \middle| h(AGE_{it}), Risk_{i(t-\tau),D}, \tau\right) \\ & = \Phi\{\alpha_D(\tau) + \beta_D(\tau) h(AGE_{it}) + \gamma_D(\tau) Risk_{i(t-\tau),D}\} \end{aligned} \tag{7}$$

In Eq (7), the uncontrolled forward model excludes the correction term (CCR), showing an intendent regression for default.

4.4.3 Formulas for survival probability and unconditional probability

The direct outcomes of the life-cycle model and forward model are marginal prepayment and default probabilities at an age/time. For multi-year forecasts, we need to determine the survival probability over the loan's lifetime. The survival probability, given survivorship in all previous periods at time t, is given as:

$$S_t = \prod_{k=1}^{t} (1 - PP_{ik} - PD_{ik}) \tag{8}$$

The unconditional prepayment and default probabilities (as it does not condition on survival by including probability of survival) at time t controlled for survivorship in all previous periods are given as:

$$PP_{it,un} = PP_{it} * S_t \tag{9a}$$

$$PD_{it,un} = PD_{it} * S_t \tag{9b}$$

In the following section, we estimate the life-cycle model and forward model. We later perform two validation tests (by age and by time) to assess the accuracy of the two approaches.

4.5 Empirical analysis

4.5.1 Data source

We analyze loan-level data of US fixed-rate prime mortgages from 2000–2016 (observed annually) provided by the US Federal Home Loan Mortgage Corporation. The 2000–2016 sample period allows us to observe a full economic cycle by accounting for the period prior to the GFC (2000–2006), during the GFC (2007–2009), and after the GFC (2010–2016). The sample includes approximately 23 million loan accounts and 100 million observations for the entire observation period. To reduce the time intensity of running regressions on big data, we randomly assess 1% of the data. The reduced sample includes 184,843 loan accounts and 847,354 observations. Beside the main mortgage dataset, we also use the house price index at the zip code level from Zillow,[32] the market interest rate of 30-year fixed-rate mortgages from Freddie Mac, and the net percentage of domestic respondents tightening standards for mortgage loans from the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices. The variables are defined in Table 4.3.

[32] We also tested the FHFA house price index (including the three-digit and five-digit zip code HPI, which should be considered as experimental or developmental) and the Case Shiller house price index with consistent results. Results are available on request.

Table 4.3 Definition of variable used

This table shows the definitions of variables used.

Panel A: Dependent variables	
PREPAYMENT	Dummy variable is one if a loan is prepaid fully before maturity and is zero otherwise.
DEFAULT90	Dummy variable is one if a loan is due for 90+ days or in foreclosure and is zero otherwise.
Panel B: Risk factors	
AGE	Time (in years) since origination to observation date.
FICO score	Credit score at origination (measures the credit quality of a borrower).
DTI	Debt-to-income ratio at origination (calculated as monthly loan payment divided by monthly income).
LTV	Current loan-to-value ratio (current loan outstanding relative to the current property value).
SIZE	Natural logarithm of the current loan amount.
IR_GAP	Difference between current interest rate and market interest rate of fixed-rate mortgage.
HPI	Current growth rate of house price index at the zip code level (from Zillow).
LENDING_STD	Net percentage of domestic respondents tightening standards for mortgage loans (from the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices).
Panel C: Dummy controls	
JOINT	Dummy variable is one if a loan has multiple borrowers and is zero otherwise.
INVESTOR	Dummy variable is one if a loan funds an investment property and is zero otherwise.
LMI	Dummy variable is one if a loan is insured by lenders' mortgage insurance and is zero otherwise.
MSA	Dummy variable is one if a property is located at a metropolitan area and is zero otherwise.
CASHOUT	Dummy variable is one if mortgages are cash-out refinancing and is zero otherwise.
NOCASHOUT	Dummy variable is one if mortgages are rate refinancing and is zero otherwise.

4.5.1.1 Dependent variables

The two dependent variables are the binary indicators. The prepayment indicator (PREPAYMENT) is one if a loan outstanding is paid off in full and is zero otherwise. The default indicator (DEFAULT90) is one if a loan is 90+ days overdue or in foreclosure and is zero otherwise.[33] Table 4.4 provides the summary statistics of prepayment and default rates by loan age and time.

Table 4.4 Summary statistics of variables by loan age and time

This table reports mean and standard deviation of dependent variables (PREPAYMENT and DEFAULT90) by loan age. Prepayment rate is calculated as the observed prepayments (#Prepayments) over the number of active loans (#Loan) in the portfolio. Default rate is calculated as the observed defaults (Defaults) over the number of active loans (Loan) in the portfolio.

	Loans	Prepayments	Defaults	Prepayment rate	Default rate
Panel A: By loan age					
1	184,843	6,066	141	3.3%	0.1%
2	166,795	27,416	960	16.4%	0.6%
3	129,797	24,935	1,478	19.2%	1.1%
4	99,158	17,053	1,361	17.2%	1.4%
5	73,282	11,260	1,210	15.4%	1.7%
6	54,531	8,506	912	15.6%	1.7%
7	42,544	7,364	744	17.3%	1.7%
8	31,669	6,304	565	19.9%	1.8%
9	21,403	4,218	396	19.7%	1.9%
10	15,576	3,018	240	19.4%	1.5%
11	11,089	2,171	138	19.6%	1.2%
12	7,732	1,201	97	15.5%	1.3%
13	4,673	736	59	15.8%	1.3%
14	2,921	400	31	13.7%	1.1%
15	988	129	10	13.1%	1.0%
16	353	43	-	12.2%	0.0%
Panel B: By time					
2000	5,657	148	13	2.6%	0.2%
2001	18,356	3,248	66	17.7%	0.4%
2002	27,946	5,971	182	21.4%	0.7%
2003	38,378	11,750	233	30.6%	0.6%
2004	35,381	5,812	206	16.4%	0.6%
2005	42,610	5,183	219	12.2%	0.5%
2006	46,689	3,726	254	8.0%	0.5%
2007	52,286	4,036	343	7.7%	0.7%
2008	57,968	4,482	669	7.7%	1.2%
2009	70,521	10,187	1,610	14.4%	2.3%
2010	69,922	10,976	1,518	15.7%	2.2%
2011	65,661	9,592	1,028	14.6%	1.6%
2012	65,592	14,589	724	22.2%	1.1%
2013	61,391	10,662	488	17.4%	0.8%
2014	57,892	5,272	337	9.1%	0.6%
2015	63,061	6,890	300	10.9%	0.5%
2016	68,043	8,296	152	12.2%	0.2%

[33] We also tested default definitions of 60+ days and 180+ days as robustness checks and the findings were consistent.

4.5.1.2 Control variables

We consider a set of age elements simulating the life-cycle effects, metric risk factors, and dummy controls. We include the loan age (time since origination, AGE). For prepayment, we use the set of $(AGE_{it}, AGE_{it}^2, \ln AGE_{it}, (\ln AGE_{it})^2)$. For default, we choose the fourth degree of polynomials function because it is the best function by which to simulate the empirical data in respect to age.

Metric risk factors include FICO score, debt-to-income (DTI) ratio, current LTV ratio, current loan size (SIZE), gap between current interest rate charged and market reference rate (IR_GAP), house price index (HPI), and proxy for lending standard (LENDING_STD). The FICO score at origination is an index to capture the credit quality of borrowers. The DTI ratio at origination is a ratio between monthly debt payments and monthly income, which is a proxy for loan serviceability. The LTV ratio is measured as the current loan outstanding divided by current house price. We approximate the current house price based on the change in house price index by Zillow at the zip code level. SIZE is the natural logarithm of the current loan amount. IR_GAP is a key factor that triggers the refinancing decision as borrowers have a greater incentive to refinance if the gap interest rate is greater. HPI is the growth of house price index sourced from Zillow. LENDING_STD is a proxy for the credit supply, which is the net percentage of domestic respondents tightening standards for mortgage loans from the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices.

We also use several dummy controls. The dummy variable JOINT is one if a loan has multiple borrowers and is zero otherwise. INVESTOR is one if loans are for investment property and zero if loans are for homeowner occupied property. We include the dummy variable LMI that is one if a loan is required to pay a lenders' mortgage insurance and is zero otherwise. We control for the locations of properties by the dummy variable MSA that is one if a property is located at a metropolitan area and is zero otherwise. We include two dummy variables controlling for loan purposes. CASHOUT is one if mortgages are cash-out refinancing loans and is zero otherwise. NOCASHOUT is one if mortgages are non-cash-out refinancing loans and is zero otherwise. The reference for refinancing loans is purchase loans.

4.5.1.3 Relationship between dependent and control variables

For prepayment, the ability to refinance is generally aligned with low credit risk. The higher the FICO score, the higher the chance of prepayment. The higher the DTI ratio, the lower the chance of prepayment. The current LTV ratio matters more in risk assessment as borrowers pay higher rates for higher LTV loans at the time of refinancing. IR_GAP is a key factor that triggers the refinancing decision as borrowers have a greater incentive to refinance if the gap between interest rates is greater. LENDING_STD is negatively related to prepayment as tightening lending standards make refinancing less accessible.

For default, FICO score, DTI ratio, and LTV ratio have opposite effects compared to prepayments. In particular, a higher FICO score implies that borrowers have a lower probability of defaulting. The higher the DTI and/or LTV ratio, the higher the default risk. We do not include IR_GAP in the default models as this variable is a strong predictor for prepayment but not for default. We do not include LENDING_STD in the default models as lending standards may indirectly affect defaults through prepayments in the way that a borrower may be defaulting because they could not prepay. Mayer et al. (2013) found that refinancing is particularly beneficial to riskier borrowers as it helps to lower their interest payment and reduce defaults. Interest rate gaps and lending standards at origination may be important. Table 4.5 summarizes the statistics of the variables from the pooled sample of observations from 2000–

2016. We have 14% prepayment rate and 0.98% default rate. The average age for prepaid loans is 4.5 years and for defaulted loans is 5.2 years. Most of the risk factors show the inverse relationship between prepayment and default. For example, at origination the average FICO score of prepaid loans is higher than that of defaulted loans. The mean of LTV for prepaid loans is much lower than for defaulted loans.

Table 4.5 Summary statistics of dependent and control variables used

This table reports the mean and standard deviation of variables from the pooled sample from 2000 to 216. The T-test is a test of mean differences between prepaid loans (PREPAYMENT=1) and defaulted loans (DEFAULT90=1).

Variable	Pooled sample		PREPAYMENT=1		DEFAULT=1		T-test
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	(Prepayment – Default)
PREPAYMENT (%)	14.26	34.96	100.00	0.00	0.00	0.00	
DEFAULT90 (%)	0.98	9.87	0.00	0.00	100.00	0.00	
AGE	3.82	2.79	4.45	2.72	5.18	2.60	–0.73***
FICO	734.84	54.92	735.76	53.81	685.92	56.17	49.84***
DTI	33.58	11.68	33.59	11.70	38.90	11.37	–5.31***
LTV	65.86	21.73	64.39	21.56	85.89	27.16	–21.50***
SIZE	11.84	0.63	11.86	0.74	11.83	0.60	0.03***
IR_GAP	0.58	1.03	1.00	0.90	1.23	1.41	–0.23***
HPI	2.32	9.02	3.24	9.81	–0.87	9.38	4.11***
LENDING_STD	7.01	21.98	4.43	18.24	11.76	21.45	–7.33***
JOINT (%)	57.61	49.42	61.17	48.74	42.40	49.42	18.77***
INVESTOR (%)	5.37	22.55	4.40	20.52	5.50	22.80	–1.10***
LMI (%)	17.72	38.18	17.14	37.68	31.92	46.62	–14.78***
MSA (%)	85.34	35.37	86.48	34.19	85.17	35.54	1.31***
CASHOUT (%)	29.39	45.56	27.84	44.82	37.31	48.36	–9.46***
NOCASHOUT (%)	33.79	47.30	33.35	47.14	26.26	44.01	7.08***

Note. * p = 0.1, ** p = 0.05, *** p =0.01.

4.5.1 Life-cycle models for mortgages

The life-cycle model estimates for prepayment and default are shown in Table 4.6.

Table 4.6 Regression results of life-cycle models

This table reports the regression results of life-cycle models for prepayment and default using the pooled sample from 2000 to 2016. LENDING_STD and IR_GAP are excluded from default model as these variables explain more intuitively for prepayment. CCR is a credit correction ratio, which is calculated from prepayment model and included in the default model to control for prepayment selection bias.

		Prepayment	Default (no selection)	Default (with selection)
Estimates of age function				
	AGE	1.6413***	1.0416***	0.8579***
		(0.1274)	(0.0487)	(0.0514)
	AGE^2	-0.0352***	-0.2142***	-0.1727***
		(0.0031)	(0.0142)	(0.0139)
	AGE^3		0.0182***	0.0143***
			(0.0015)	(0.0014)
	AGE^4		-0.0005***	-0.0004***
			(0.0001)	(0.0000)
	LnAGE	0.5335***		
		(0.0932)		
	(LnAGE)^2	-2.2695***		
		(0.1258)		
Estimates of metric risk factors				
	FICO	0.0006***	-0.0045***	-0.0046***
		(0.0001)	(0.0001)	(0.0001)
	DTI	-0.0004*	0.0080***	0.0079***
		(0.0002)	(0.0004)	(0.0004)
	LTV	-0.0052***	0.0127***	0.0130***
		(0.0005)	(0.0006)	(0.0005)
	SIZE	0.1660***	-0.0483***	-0.0660***
		(0.0168)	(0.0140)	(0.0136)
	HPI	0.0067***	-0.0054***	-0.0082***
		(0.0023)	(0.0011)	(0.0015)
	LENDING_STD	-0.0026***		
		(0.0004)		
	IR_GAP	0.3269***		
		(0.0173)		
	CCR			-0.6693***
				(0.0881)
Estimates of dummy controls				
	JOINT	0.1075***	-0.2147***	-0.2361***
		(0.0073)	(0.0094)	(0.0096)
	INVESTOR	-0.2961***	0.1022***	0.1233***
		(0.0188)	(0.0277)	(0.0277)
	LMI	-0.0068	0.0717***	0.0757***
		(0.0154)	(0.0146)	(0.0150)
	MSA	0.0658***	-0.0200	-0.0315**
		(0.0109)	(0.0139)	(0.0137)
	CASHOUT	-0.1133***	0.1992***	0.2222***
		(0.0138)	(0.0170)	(0.0163)
	NOCASHOUT	-0.0369***	0.0991***	0.1191***
		(0.0110)	(0.0136)	(0.0130)
AUROC		71.40%	86.30%	86.50%
Obs		847,345	847,345	847,345

Note. Standard errors are presented in parentheses. * p =0.1, ** p = 0.5, *** p = 0.01.

Regarding the age function, all estimates of AGE-related factors are significant. In particular, the estimate of AGE is positive and significant for both prepayment and default models, implying a positive relation between age and probabilities. The estimate of AGE^2 is negative and significant for all models, suggesting that prepayment and default patterns follow a hump shape in which probabilities increase to a peak then decline.

Regarding metric risk factors, all estimates are significant and show opposite signs for prepayment and default. FICO is positively correlated with prepayment and negatively correlated with default. The estimates of DTI and LTV are negative for the prepayment model and positive for the default model, which suggests high-risk loans are less likely to be prepaid and more likely to be defaulted on. The estimate of HPI is positive for prepayment, which means prepayment tends to occur when house prices increase as borrowers can extract home equity. Conversely, the estimate of HPI is negative for default, indicating a higher tendency of negative equity. The estimates of LENDING_STD are negatively correlated to prepayment. The estimates of IR_GAP are all positive and significant, implying that borrowers are likely to refinance when market interest rates fall below the contracted fixed rates. We did not include LENDING_STD and IR_GAP in the default model as those factors explain more intuitively for prepayment, but not default.

Regarding dummy controls, all estimates show opposite signs for prepayment and default. For example, the estimate of JOINT is positive and significant for prepayment, indicating that a loan jointly borrowed by multiple borrowers (e.g., couples) is easier to refinance. Conversely, the estimate of JOINT is negative and significant for default, meaning a lower likelihood of default. The estimates of INVESTOR are negative for prepayment and positive for default, suggesting that an investment loan is has a lower prepayment risk and higher default risk than a home-occupied loan. The estimates of MSA are positive for prepayment and negative for default, meaning that mortgages for properties located in metropolitan areas are easier to refinance and harder to default on. The estimates of refinanced loans (CASHOUT and NOCASHOUT) are negative for prepayment, which means that borrowers who have refinanced once are less likely to refinance again compared to primary purchase cases.

We control for the prepayment selection bias in the default model by CCR. The estimate of CCR is negative and significant, which suggests correlated unobservable factors between the two processes.

The discriminative accuracy of the models is reflected through the AUROC. The AUROC for the prepayment model is 71.4%, for the default model without control for selection is 86.3% and for the default model with control for selection is 86.5%.

The calibration accuracy of the models is their ability to predict probabilities equal to that of the actual rates. We measure the relative deviation as the difference between the mean of predicted probabilities and actual rates divided by actual rates in every age or time. We then calculated the MAE as the average of absolute values of deviation across all ages/times for an overall calibration. The in-sample calibration is reported in Table 4.7.

Table 4.7 In-sample calibration of life-cycle models

This table reports the in-sample calibration of the life-cycle model for prepayment and default by age and by year. MAE is the mean absolute error, which is calculated as the mean of all absolute values of deviations across ages/times. The MAE measures overall calibration accuracy.

Panel A: Prepayment life-cycle model	
MAE across all ages	3.9%
MAE across all years	29.8%
Panel B: Default life-cycle model (no selection)	
MAE across all ages	18.9%
MAE across all years	24.2%
Panel C: Default life-cycle model (with selection)	
MAE across all ages	12.5%
MAE across all years	23.5%
Observed periods	2000 - 2016
Obs	847,354

The MAE across all ages of prepayment model is 3.9%, which is considerably lower than the MAE of default model at 12.5%. The MAE across years for prepayment model is 29.8% and for default model is 23.5%. Default model with control for selection is calibrated more accurately than default model without selection.

In short, the regression results of the life-cycle models show that most risk factors explain for prepayment and default in opposite directions. For the default model, the model controlling for prepayment selection provides a better fit by reducing MAE from 19% to 12%.

4.5.2 Forward models for mortgages

We estimate the forward models for prepayment and default using the same set of age and risk factors used in the life-cycle models. We use lagged covariates to construct models for different horizons from one-year to 10-year periods. The regression results of the forward prepayment models are shown in Table 4.8.

Panel A shows the parameter estimates of forward prepayment model. Panel B shows the parameter estimates of forward default model without control for selection. Panel C shows the parameter estimates of forward default model with control for selection (CCR). It is noted that the estimates of one-year forward model is identical to the life-cycle models as they are using the most recent covariates.

Table 4.8 Regression results of forward models

This table reports the statistics of the parameter estimates of key risk factors from one-year to 10-year forward models for prepayment (Panel A), default without selection (Panel B) and default with controlling for prepayment selection (Panel C).

	Horizon									
	1-year	2-year	3-year	4-year	5-year	6-year	7-year	8-year	9-year	10-year
Panel A: Forward prepayment models										
AGE	1.641***	2.719***	1.794***	–3.053***	–5.540***	–6.476***	–3.782	–0.766	–3.174**	–5.514***
AGE^2	–0.035***	–0.058***	–0.043***	0.033***	0.071***	0.094***	0.059	0.015	0.068**	0.112***
LN(AGE)	0.534***	0.587***	–1.023**	–10.156***	–15.551***	–12.350	–0.515	4.652	18.152**	33.043***
(LN(AGE))^2	–2.270***	–3.628***	–1.868***	7.358***	12.280***	12.588**	5.705	0.000***	0.000***	0.000***
FICO	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
DTI	0.000*	–0.001***	–0.001***	–0.002***	–0.002***	–0.002***	–0.003***	–0.003***	–0.004***	–0.005***
LTV	–0.005***	–0.006***	–0.003***	–0.002***	–0.002***	–0.003***	–0.003***	–0.002***	–0.002***	–0.001*
SIZE	0.166***	0.216***	0.188***	0.205***	0.227***	0.249***	0.257***	0.269***	0.249***	0.252***
HPI	0.007***	0.010***	0.002	–0.001	0.001	0.000	–0.004***	–0.002*	0.004***	0.003***
LENDING_STD	–0.003***	0.002***	0.003***	0.003***	0.005***	0.006***	0.000	–0.003***	–0.001**	0.000
IR_GAP	0.327***	0.386***	0.218***	0.138***	0.084***	0.022**	–0.035***	–0.042***	–0.057***	0.004
Dummy controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUROC	71.4%	66.4%	60.9%	60.3%	61.3%	62.3%	61.6%	62.8%	62.4%	62.0%
No. of observations	847,354	662,510	495,715	365,917	266,757	193,463	138,930	96,385	64,724	43,321
Panel B: Forward default models (no selection)										
AGE	1.042***	0.723***	0.446***	0.574***	0.370	1.848***	5.121***	12.437***	14.456	11.164
AGE^2	–0.214***	–0.143***	–0.085***	–0.103***	–0.058	–0.278***	–0.744***	–1.732***	–1.989*	–1.599
AGE^3	0.018***	0.012***	0.007***	0.007**	0.004	0.018***	0.047***	0.105***	0.120*	0.099
AGE^4	–0.001***	0.000***	0.000***	0.000**	0.000	0.000***	–0.001***	–0.002***	–0.003*	–0.002
FICO	–0.005***	–0.005***	–0.004***	–0.004***	–0.004***	–0.003***	–0.003***	–0.002***	–0.002***	–0.002***
DTI	0.008***	0.009***	0.009***	0.009***	0.008***	0.007***	0.006***	0.005***	0.005***	0.005***
LTV	0.013***	0.011***	0.008***	0.006***	0.004***	0.003***	0.003***	0.004***	0.004***	0.004***
SIZE	–0.048***	–0.045***	–0.023*	–0.002	0.029	0.025	0.000	–0.041	–0.048	–0.083**
HPI	–0.005***	–0.016***	–0.019***	–0.018***	–0.008***	–0.002**	0.001*	0.002**	0.004**	0.005**
Dummy controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Horizon									
	1-year	2-year	3-year	4-year	5-year	6-year	7-year	8-year	9-year	10-year
AUROC	86.3%	83.0%	80.5%	77.3%	72.8%	69.6%	68.0%	66.0%	65.1%	64.1%
No. of observations	847,354	662,510	495,715	365,917	266,757	193,463	138,930	96,385	64,724	43,321
Panel C: Forward default models (with prepayment selection)										
AGE	0.858***	0.568***	0.780***	1.309***	0.574**	1.877***	6.007***	12.427***	15.202*	15.021
AGE^2	–0.173***	–0.106***	–0.141***	–0.238***	–0.097**	–0.285***	–0.833***	–1.734***	–2.062*	–2.009
AGE^3	0.014***	0.008***	0.010***	0.017***	0.007*	0.018***	0.050***	0.105***	0.122*	0.118
AGE^4	0.000***	0.000***	0.000***	0.000***	0.000	0.000***	–0.001***	–0.002***	–0.003**	–0.003
FICO	–0.005***	–0.005***	–0.005***	–0.005***	–0.004***	–0.003***	–0.002***	–0.003***	–0.001*	0.000
DTI	0.008***	0.008***	0.009***	0.009***	0.008***	0.007***	0.004***	0.005***	0.003**	0.002
LTV	0.013***	0.011***	0.009***	0.006***	0.004***	0.003***	0.001	0.004***	0.003**	0.004**
SIZE	–0.066***	–0.096***	–0.113***	–0.097***	–0.003	0.011	0.180***	–0.067	0.061	0.074
HPI	–0.008***	–0.021***	–0.018***	–0.015***	–0.007***	–0.002	–0.001	0.002**	0.006***	0.007***
CCR	–0.669***	–1.200***	–1.830***	–1.583***	–0.442	–0.164	1.817***	–0.239	1.093*	1.705*
Dummy controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUROC	86.5%	83.8%	81.3%	77.7%	72.9%	69.6%	68.0%	66.0%	65.1%	64.0%
No. of observations	847,354	662,510	495,715	365,917	266,757	193,463	138,930	96,385	64,724	43,321

Note. * $p = 0.1$, ** $p = 0.5$, *** $p = 0.01$.

To illustrate the time-varying coefficients, the parameter estimates of several key factors for prepayment in the forward models are plotted in Figure 4.1.

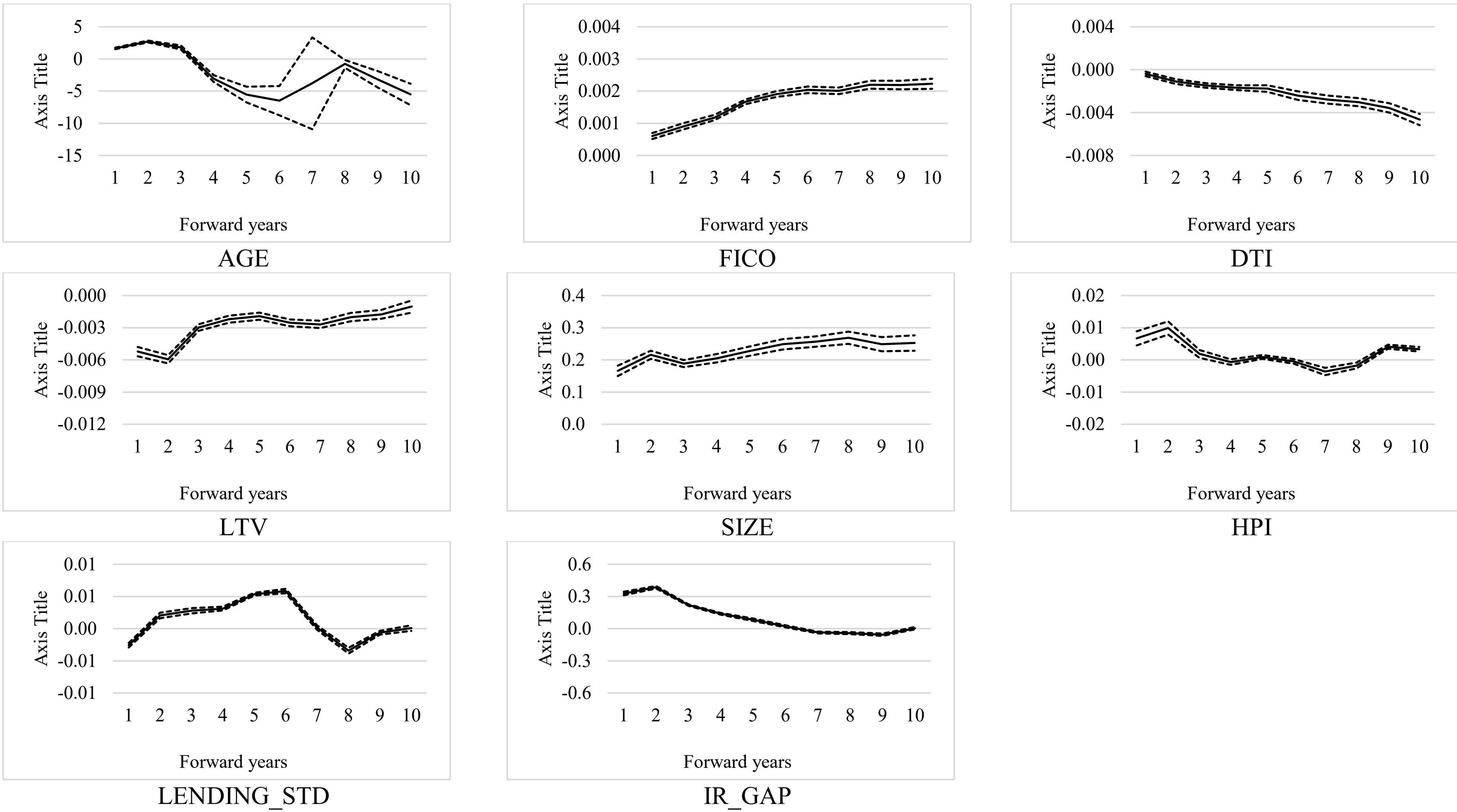


Figure 4.1. Estimates of key factors in forward prepayment models

This figure shows estimates of key factors in forward prepayment models. Solid black line = point estimates, dash lines = 95% confidence intervals.

For the forward prepayment models, AGE is significant and positively correlated to prepayment predictions for the first three years and loses its predictive significance for longer horizons. The estimates of FICO are all positive and significant, showing its stable predictive ability in the long run. The better the credit quality of borrowers, the higher the chance that they will prepay in longer future times. All estimates of DTI are negative, which is reasonable for prepayment, but its effect decreases for longer future periods. All estimates of LTV are negative and increase over horizons, suggesting that the current (i.e., present-day) LTV has a higher effect on prepayment in longer future times than short future times. The estimates of SIZE are positive, meaning that the higher the loan amount, the higher the incentive to refinance at a lower interest rate. The estimates of HPI are positive in the first three years and then fluctuate to around zero, suggesting that HPI works better for short horizon predictions. The estimates of LENDING_STD are negative for the one-year forward model and increase over forward years. This can be explained by the tightened lending standards at present time constraining prepayment decisions in the next period but increasing the chance of prepayment in longer future periods. The estimates of IR_GAP are positive for short and medium horizons (i.e., less than six years), meaning that borrowers may not prepay in next period but instead delay the decision to longer future periods.

The estimates of several key factors for the default model controlling for prepayment selection are plotted in Figure 4.2.

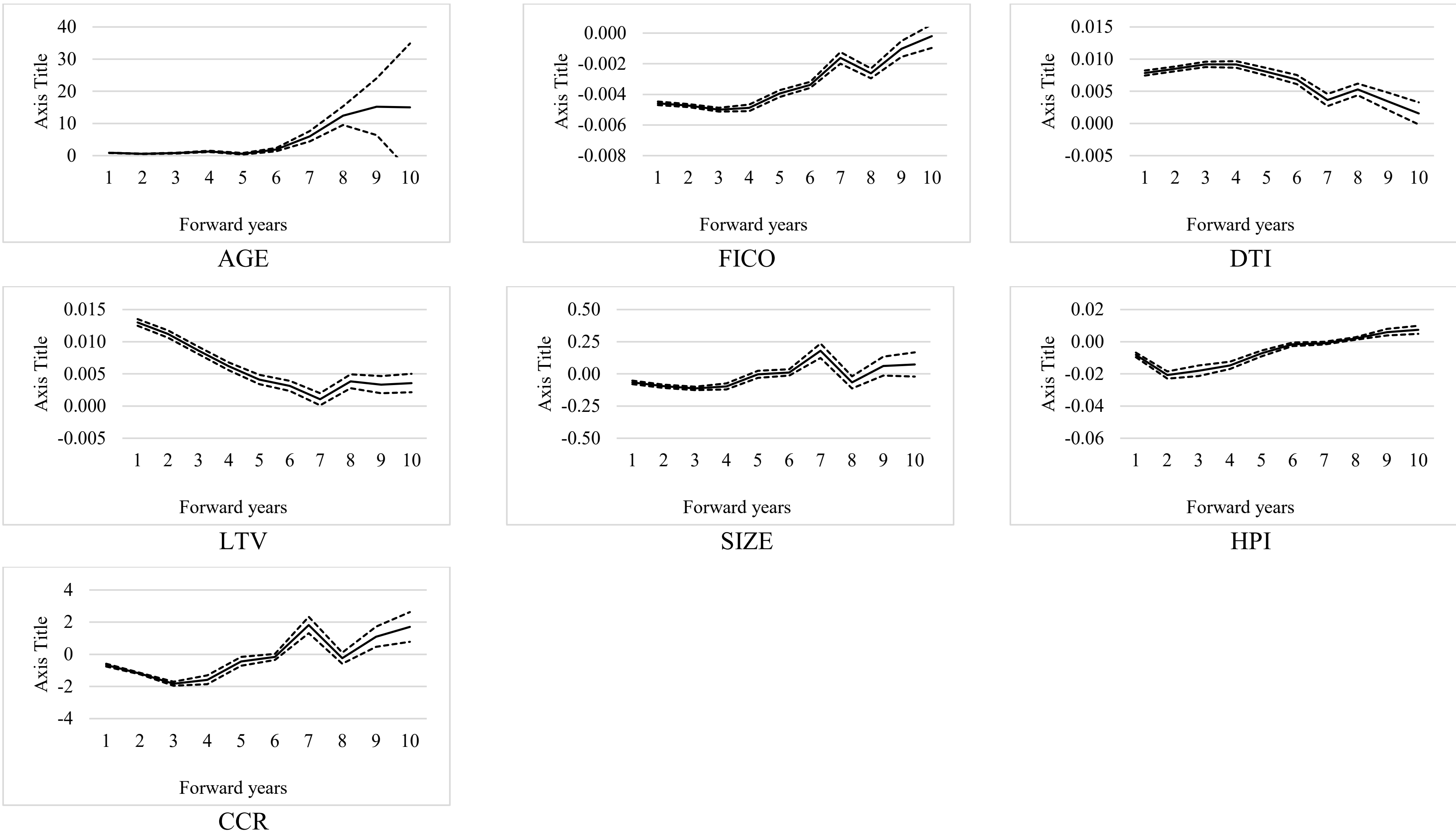


Figure 4.2. Estimates of key factors in forward default models

This figure shows estimates of key factors in forward default models. Solid black line = point estimates, dash lines = 95% confidence intervals.

For the forward default models, the estimates of AGE are significant for short and medium horizons (i.e., under six years) and insignificant for longer periods. The estimates of FICO are mostly negative and significant, suggesting a strong predictor for the long run. The estimates of DTI and LTV are always positive, but decrease over future periods, implying a loss of predictive ability for longer future periods. Similarly, SIZE and HPI lose their predictive ability for forward models after three years. The estimates of CCR (a credit correction ratio for prepayment selection at future times) are negative and significant for one-year to three-year forecasts, but do not help in predicting default in further future periods.

In short, most risk factors show good predictive ability for prepayment and default for up to three years ahead. For longer horizons, lagged covariates lose their significance or the rational sign. Among common risk factors, FICO appears to the most consistent in its predictive ability for both short and long terms.

The discriminative accuracy of forward models decreases the further the horizon. For prepayment, AUROC is highest (at 71%) for the one-year model. Beyond one period, AUROC decreases significantly to just over 60%. For default, AUROC is highest (at 86.5%) for the one-year model, decreases gradually to 70% up to the five-year model, and reduces further to around 60% for up to the 10-year model.

There are different validation methods: discrimination, calibration and stability. R^2 is not an appropriate performance measure for binary variables such as payoff or default. Please note that discrimination measured by AUROC may not be comparable across different samples. Calibration measured by MAE is a more comprehensive metric to assess how well a model provides an accurate prediction of risk levels. Also, MAE is aligned with other metrics like bank earnings, spreads, etc. This is why we focus on calibration performance.

Table 4.9 In-sample calibration of forward models

This table reports the in-sample calibration by time of the forward models for prepayment and default. The aim of a forward model is to calibrate probabilities to actual rates by time. The number of observations drops with the time horizon. The MAE is calculated as the mean of absolute deviation between predicted probabilities and actual rates across years.

	Horizon									
	1-year	2-year	3-year	4-year	5-year	6-year	7-year	8-year	9-year	10-year
Panel A: Forward prepayment models										
MAE across ages	3.9%	6.9%	7.3%	3.5%	3.8%	3.8%	3.2%	4.7%	3.6%	4.8%
MAE across years	29.8%	25.1%	36.6%	38.2%	30.1%	21.7%	19.5%	16.1%	14.5%	23.9%
Panel B: Forward default models (no selection)										
MAE across ages	18.9%	8.1%	6.4%	6.1%	6.5%	6.0%	5.3%	5.2%	6.2%	6.7%
MAE across years	24.2%	27.8%	33.5%	37.8%	47.8%	41.2%	30.2%	28.8%	20.1%	19.0%
Panel C: Forward default models (with prepayment selection)										
MAE across ages	12.5%	6.5%	6.4%	5.5%	6.2%	6.0%	5.2%	5.3%	6.1%	6.7%
MAE across years	23.5%	25.1%	32.0%	38.3%	48.1%	40.8%	31.3%	28.9%	21.7%	19.0%
Observed period	2000–2016	2001–2016	2002–2016	2003–2016	2004–2016	2005–2016	2006–2016	2007–2016	2008–2016	2009–2016
No. of observations	847,354	662,510	495,715	365,917	266,757	193,463	138,930	96,385	64,724	43,321

The calibration accuracy of the forward model is shown in Table 4.9. As the model uses lagged variables, only the one-year model has accurately predicted the probabilities on every observation. Models predicting for long horizons lose the number of observations. The MAE is calculated as the mean of absolute deviations between predicted probabilities and actual rates across ages/years of observed periods.

For forward prepayment models, the calibration over ages is good as the MAEs vary slightly from 3–7% over short to long future periods. The calibration over years shows the lowest MAE of 15% for the nine-year forward model, which is due to this model covering the period 2008–2016 which had the least fluctuation of prepayment rates. The highest MAE is 38% for the four-year forward model, which is due to this model covering the period 2003–2016, which had erratic movement in prepayment rates.

Regarding default models, for predictions of up to three years, the model controlling for prepayment provides a better fit than the model without control for selection.

Overall, in-sample calibration by times does not reflect the true accuracy as we lose observations in the sample when using different orders of lagged covariates.

4.6 Validation

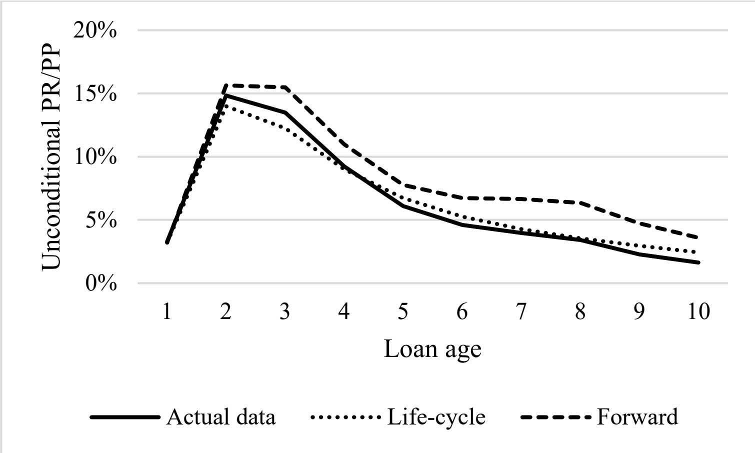
4.6.1 Validation 1: multi-year forecasts for loans since origination by age

This section presents our first validation test for multi-year forecasts. Our aim is to validate the prediction ability of the two models for new loans since origination over future ages. We pool all loans from the sample data and start observations from origination (AGE=1). We then create an output dataset with repeated information of each loan over the next 10 years, except for age. AGE will change the value by cumulatively adding one period to period. Other covariates are assumed to be the same at origination time. In the final output data, every loan has 10 observations for 10 ages.

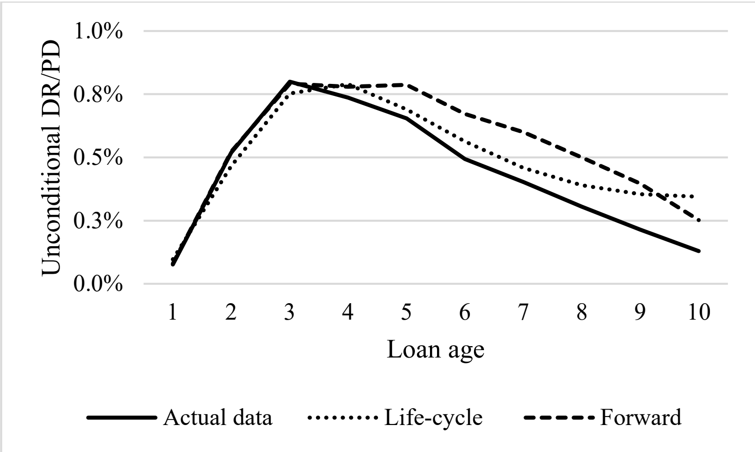
We then use the life-cycle models and forward models to perform 10-year forecasts of prepayment and default risk. For the life-cycle models, the dynamic change in AGE is the key factor for predicting marginal probabilities in each period. The effects of the covariates are reflected in only one coefficient for each factor. For forward models, besides the change in AGE, we have different coefficients for different future ages.

The direct outcomes of the life-cycle models and forward models are marginal prepayment and probabilities at each age. We then estimate the survival probability for each loan at a certain age using Eq (8). The next step is to calculate unconditional prepayment and default probabilities using Eq (9a) and Eq (9b) adjusted for the survivorship of all previous ages.

Figure 4.3 shows the multi-period forecasts by ages. All loans are observed since origination and probabilities are forecasted for up to 10 years. Figure 4.3a shows the multi-age forecasts since loan origination for prepayment risk. Figure 4.3b shows the multi-age forecasts sinceloan origination for default risk by the life-cycle model and forward model. Figure 4.3c shows the multi-age forecasts since loan origination for default risk by model with and without control for prepayment selection.



(a)



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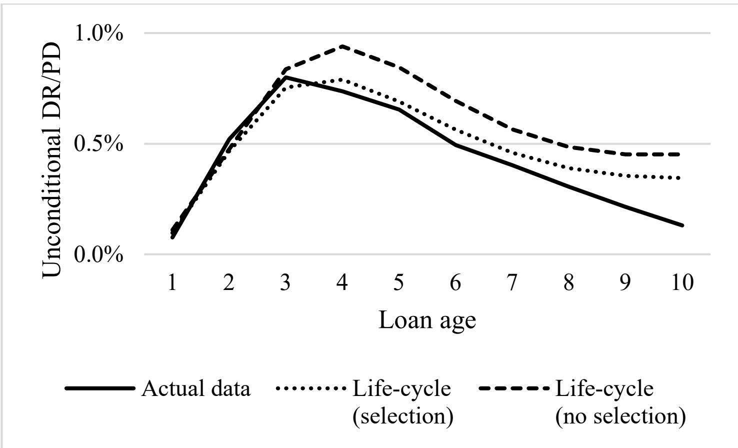


(c)

Figure 4.3. Validation 1: multi-year forecasts for loans since origination

This figure shows the actual prepayment/default rates and predicted probabilities. All loans are observed since origination and forecasted in future ages. Figure 3a shows the multi-age forecasts for prepayment risk. Figure 3b shows the multi-age forecasts for default risk by the life-cycle and forward models. Figure 3c shows the multi-age forecasts for default risk by model with and without prepayment selection.

For prepayment, the life-cycle model provides a better forecast than the forward model. The accuracy is similar between two methods for up to three-year forecasts. The life-cycle model is more accurate in predictions than the forward model for older future ages.

For default, we also see a better prediction by the life-cycle model for future ages beyond three years. Specifically, the life-cycle default model with control for selection is more accurate to predict default probabilities in the long run than the model without control for selection.

We also report the MAE for prepayment and default predictions by two models in Table 4.10.

Table 4.10 Validation 1: multi-year forecasts for loans since origination by age

Panel A reports the mean absolute errors (MAE) of unconditional probabilities in multi-year forecasts for new loans since origination up to ten-year old. Panel B reports discriminatory power measured in AUROC.

	Prepayment		Default			
	Life cycle	Forward	Life cycle (no selection)	Life cycle (with selection)	Forward (no selection)	Forward (with selection)
Panel A: Mean absolute errors						
Across all loans and ages	13.5%	49.6%	61.3%	34.1%	37.8%	36.0%
<3 years	5.6%	7.4%	19.1%	14.2%	14.2%	1.9%
4–7 years	8.7%	39.9%	34.4%	10.1%	10.1%	27.8%
8–10 years	27.8%	104.7%	139.3%	86.0%	86.0%	80.9%
Panel B: Discriminatory power (AUROC)						
AUROC	70.81%	71.40%	83.52%	83.78%	83.79%	84.82%

For prepayment, the MAE across all ages for all loans for the life-cycle model is 13.5%, which is significantly lower than that of the forward model (49.6%). For the subgroup of less than three years, both models achieve competitive accuracy, with a MAE of 5–7%. As age increases, the life-cycle model outperforms the forward model.

For default, both models are competitive in their predictions with a marginal difference in MAE (34% for the life-cycle model and 36% for the forward model). For the subgroup of less than three years, the forward model outperforms the life-cycle model.

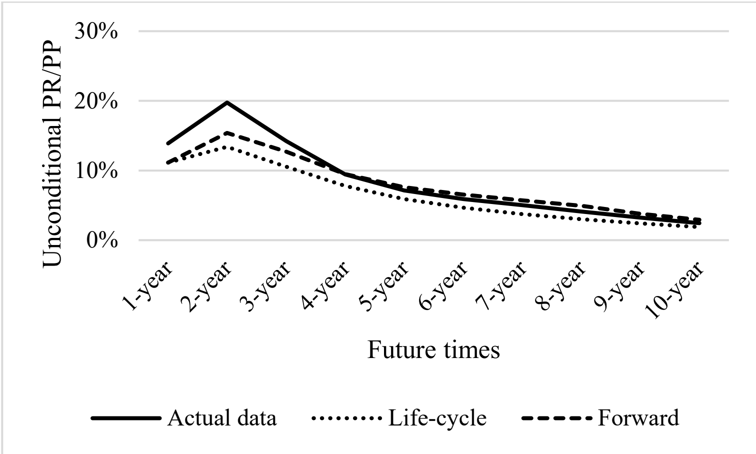
Specifically, the life-cycle default model with selection can reduce the MAE significantly by nearly 50% compared to the life-cycle default model without selection (from 61% to 34%).

In short, the life-cycle model is better in multi-year prepayment and default predictions over ages. Default model with prepayment selection is better than without control for selection.

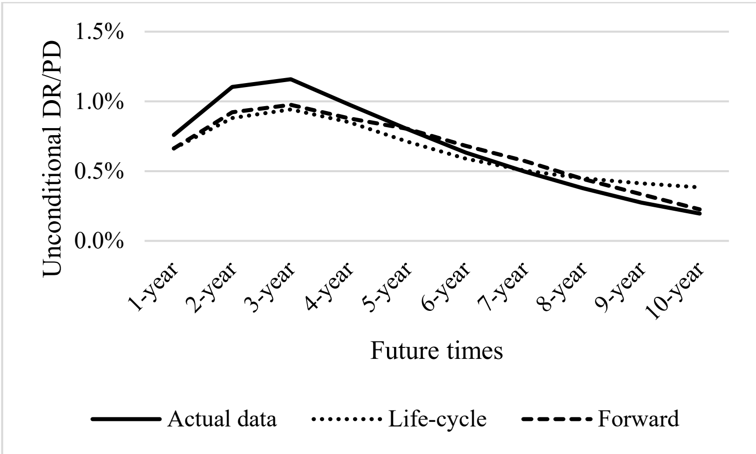
4.6.2 Validation 2: multi-year forecasts for the portfolio by time

We perform the second validation test by time. A portfolio is a mix of multi-age loans at the same time. At each year from 2000–2009 we predict the prepayment and default probabilities for active loans for the next 10 years. For example, for loans in the base year of 2000, we forecast prepayment and default probabilities for 2000–2009; for loans in the base year of 2001, the forecasting period is from 2001–2010; and so on.

We then estimate the survival probability for each loan at a certain age using Eq (8). The next step is to calculate unconditional prepayment and default probabilities using Eq (9a) and Eq (9b) adjusted for the survivorship of all previous forward times.



(a)



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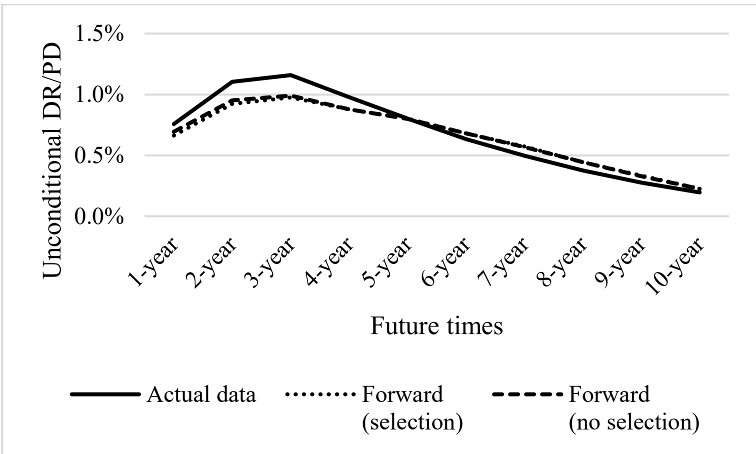


(c)

Figure 4.4. Validation 2: multi-year forecasts for portfolios at a base year by future years

This figure shows the actual prepayment/default rates and predicted probabilities by times. We choose the base time is each year-end from 2000 to 2009, and forecast for the next ten years ahead. We then take the average of actual rate and probabilities across all base years by future periods. Figure 4a shows the multi-age forecasts for prepayment risk. Figure 3b shows the multi-age forecasts for default risk by the life-cycle and forward models. Figure 4c shows the multi-age forecasts for default risk by model with and without prepayment selection.

The unconditional probabilities and cumulative probabilities are plotted in Figure 4.4. Figure 4.4a shows the multi-age forecasts for prepayment risk. Figure 4.4b shows the multi-age forecasts for default risk by the life-cycle and forward models. Figure 4.4c shows the multi-age forecasts for default risk by model with and without control for prepayment selection.

For prepayment, the highest prepayment probability occurs two years after the current time. The longer horizon, the lower the prepayment likelihood for loans in the portfolio. The forward model outperforms the life-cycle model in capturing forward-looking prepayment patterns over time.

For default, the highest default probability occurs three years after the current time. The longer horizon, the lower the default likelihood for loans in the portfolio. The forward model is better than the life-cycle model in capturing forward-looking default pattern time-to-time. In particular, the forward model with and without control for prepayment selection are similar in terms of accuracy of multi-year default forecasts.

We calculate the average of actual rates and predicted probabilities by future times from all base years, then compute a deviation for each future time as the difference between predicted probabilities and actual rates divided by actual rate. The MAE is the average of the absolute values of deviations. The MAE of the unconditional probabilities in multi-year forecasts by time is shown in Table 4.11.

Table 4.11 Validation 2: multi-year forecasts for portfolios at a base year by future year

This table reports the mean absolute errors (MAE) of unconditional probabilities in multi-year forecasts by time. At the each year-end from 2000 to 2009, we predict prepayment and default probabilities for active loans in the next ten years. Panel B reports discriminatory power measured in AUROC.

	Prepayment		Default			
	Life cycle	Forward	Life cycle (no selection)	Life cycle (with selection)	Forward (no selection)	Forward (with selection)
Panel A: Mean absolute errors						
Across all 10 years	23%	14%	36%	25%	14%	13%
<3 years	26%	18%	11%	17%	15%	15%
4–7 years	20%	8%	11%	8%	10%	8%
8–10 years	25%	19%	96%	55%	18%	18%
Panel B: Discriminatory power						
AUROC	68.84%	71.73%	79.71%	79.90%	80.63%	82.15%

For prepayment, the MAE across future times of the life-cycle model is 23%, which is greater than that of the forward model (14%). This result suggests that the calibration for a portfolio with a mix of multi-age loans over time is more accurate if using time-varying coefficients obtained from a forward model.

For default, the MAE across future times of the life-cycle model is 25%, which is greater than that of the forward model (13%). This result suggests that the calibration for a portfolio with a mix of multi-age loans over time is more accurate if using time-varying coefficients obtained from a forward model.

Comparing default models with and without control for prepayment selection, the model with selection provides a more accurate forecast.

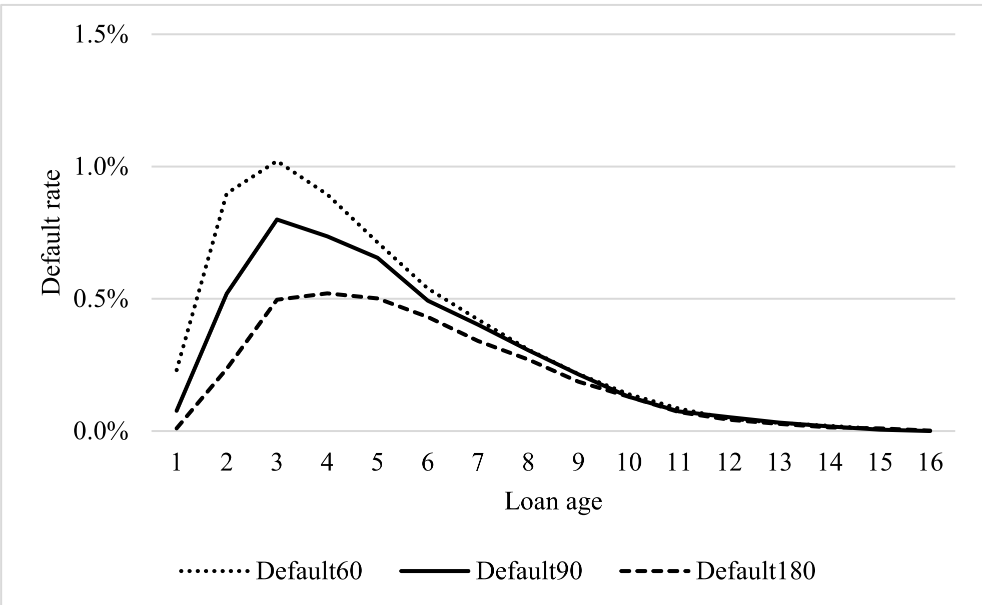
In short, for multi-year forecasts by time, we recommend a forward model as it provides better calibration for future periods.

4.6.3 Robustness check

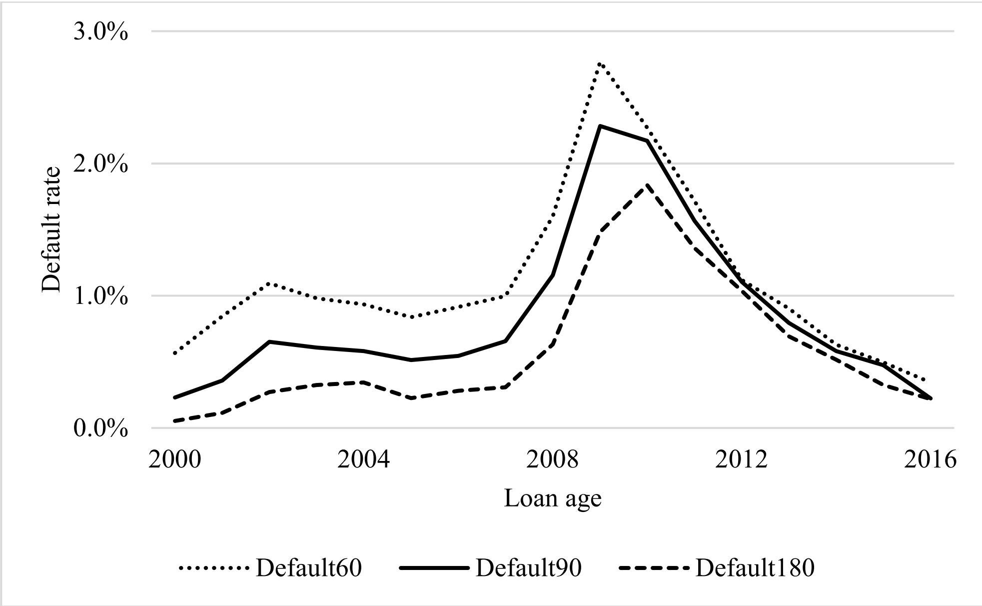
In the model estimations and validation tests above, we use the proxy for default is the DEFAULT90 that takes the value of one if a loan is 90+ days overdue or in foreclosure. In this section, we replicate estimation steps and validation steps for two other proxies of default:

- DEFAULT60 that takes the value of one if a loan is 60+ days overdue or in foreclosure.
- DEFAULT180 that takes the value of one if a loan is 180+ days overdue or in foreclosure.

Figure 4.5 shows the actual default rates by different default proxies. Figure 4.5a shows default rates by loans age (with the base of all loans at AGE=1). Figure 4.5b shows marginal default by time (with the base of the number of active loans at a year).



(a)



(b)

Figure 4.5. Robustness check: different proxies of default

This figure shows the actual default rates by different default proxies. Figure 4.5a shows default rates by loans age (with the base of all loans at AGE=1). Figure 4.5b shows marginal default rates by time (with the base of the number of active loans at a year).

It can be seen that DEFAULT60 is the highest, followed by DEFAULT90 and DEFAULT180. The difference in default rates of alternative proxies happens in the first five years of the loan lifetime. When loans become older, there are similar levels of default rates for the proxies.

We estimate the life-cycle model and forward model for DEFAULT60 and DEFAULT180. The parameter estimates are similar to the main test for DEFAULT90.[34] We then perform two validation tests (by age and by time) and report the MAE for the calibration results in Table 4.12.

[34] Results is available on request

Table 4.12 Robustness check: validation tests for different default proxies

This table reports the mean absolute errors (MAE) of unconditional probabilities in multi-year default forecasts by age and by time. Validation 1 is for multi-year default forecasts for new loans since origination up to ten-year. Validation 2 is for multi-period default forecasts by time from the base time to the next ten years.

	Life-cycle		Forward	
	No selection	With selection	No selection	With selection
Panel A: Validation 1: multi-period default forecasts by age				
MAE using DEFAULT90	61%	34%	38%	36%
MAE using DEFAULT60	54%	24%	34%	33%
MAE using DEFAULT180	84%	61%	60%	55%
Panel B: Validation 2: multi-period default forecasts by time				
MAE using DEFAULT90	36%	25%	14%	13%
MAE using DEFAULT60	33%	16%	15%	13%
MAE using DEFAULT180	40%	33%	17%	15%

The results for the different default proxies are consistent with main tests using DEFAULT90. We find that the life-cycle model provides a better calibration by age and the forward model provides a better calibration by time. All models with control for prepayment selection are more accurate than models without selection.

4.7 Conclusions

This study analyzed prepayment risk and default risk in mortgages, and constructs the models for multi-period forecasts. We use the data of US prime mortgages from 2000 to 2016.

First, we estimated a life-cycle model using loan age as a proxy for the life-cycle effect over the loan lifetime. The model outcomes are marginal prepayment and default probabilities at a certain age.

Second, we estimate a forward model using different orders of lagged variables to predict prepayment and default at different future periods. The model results in multiple coefficients for each prediction horizon. We assess the predictability of mortgage risk factors in multi-period forecasts. The direct outcomes of the two models are marginal prepayment and default probabilities at a certain time. We then back out the survival probability of a loan at a certain age given survivorship at all previous ages/times. The unconditional probabilities are adjusted for survival probability at future ages/times.

We test the predictability of two methods (life-cycle model vs. forward model) in two validation tests. The first test is the multi-period forecasts by age for new loans since origination. We recommend the life-cycle model for both prepayment and default. The second validation exercise looks at multi-period forecasts by time for the portfolio consisting of multi-age loans at a base time. We find that the forward model provides a better calibration accuracy for predictions over times.

We also employ the two-stage model that allows default regression controlling for prepayment selection. We also run an independent default regression without selection. We find that the default model with selection provides a better calibration than the model without selection.

Our findings add insight to the literature on multi-year prepayment and default forecasts. We find that the life-cycle model is better to reflect mortgage risk over ages. In contrast, the forward model is better to predict mortgage risk over times. Default models controlling for prepayment selection can improve default predictions compared to uncontrolled models. Using the life-cycle modelling approach, the uncontrolled models may overestimate the default risk in the long run. Controlling for prepayment selection can predict more accurately default risk in long run (e.g. more than three years) and can reduce the MAE by a half.

Our study has implications for bank risk measurement. For new loans joining to the portfolio, banks only know information at origination. Hence, we recommend the method of the life-cycle model to predict mortgage risk for multi-year ahead. For existing older loans in the portfolio, information is updated to the latest period. Hence, we recommend the forward model for those loans in multi-period forecasts. We emphasize the importance of prepayment selection in default prediction and suggest models controlling for selection bias. Our findings help to implement the latest accounting standards under IFRS9 and U.S. GAAP.

Chapter 5: Conclusions

5.1 Summary of the thesis focus

This thesis analyzes the impact of selection bias in bank risk measurement and management through three studies related to the liabilities and assets of bank activities. The first study explores the impact of an explicit Australian Government guarantee scheme. The second study investigates prepayment selection in default prediction. The third study explores prepayment risk and default risk over the lifetime of mortgages.

The three studies are linked in several ways. The most important link is that selection processes play a role in each of them. Participation or exit decisions of lenders and borrowers can affect the information available to empirical researchers. In order to avoid biased estimation results, it is crucial to deal with selection effects and find an appropriate way to correct for it.

The findings in the thesis contribute to the literature of bank risk management. In addition, the thesis extends existing technical approaches to provide appropriate solutions to solve the selection bias. These solutions are useful for banks to assess risk more accurately as well as for regulators to improve the efficiency and resilience of the banking system.

5.2 Summary of key findings

The thesis provides three key findings through three studies related to the liabilities and assets of bank activities. The first common finding is that selection caused by lender and borrower choices has significant effects on the outcome processes of bank risk. In the first study, we find that the voluntary decision of Australian banks to enter into the wholesale funding guarantee helped banks to reduce funding costs and funding premiums, but not did not cause excessive risk taking in terms of general bank risk, asset risk, or liquidity risk. The second study shows a change in default risk in respect to prepayment selection by borrower choices. We find that the prepayment selection significantly affected borrowers with high prepayment risk who did not refinance and remained in the sample post prepayment.

The second finding is that the selection effects of lender and borrower choices differ according to banks and states of macroeconomics. In the first study, large banks had a higher probability of participating in the guarantee program during the GFC to maintain consumer/investor confidence and drew greater benefit from it than small banks. In the second study, default risk in upturns is higher for the subgroup of high-prepayment-risk borrowers, while in downturns the more constrained ability to prepay results in a higher default risk for the subgroup of low-prepayment-risk borrowers.

The third finding is that controlling for selection effects is important to improve risk predictions in both the short and long run. In the second study, we propose a two-stage model with a novel correction term that can improve the calibration accuracy of default predictions for one period ahead. In the third study, we employ further alternative approaches to predict mortgage prepayment risk and default risk beyond one period. We found that a life-cycle approach using dynamic changes in age can help to predict prepayment risk over the loan lifetime. In addition, a default model controlling for prepayment selection provides more accurately multi-period default predictions compared to an uncontrolled model.

5.3 Implications of the thesis

The findings have several implications for banks and regulators in risk measurement and management.

For industry practice, this thesis suggests new approaches to better assess the credit risk of borrowers. In Chapter 3, a two-stage model with a novel correction term is proposed to correct prepayment selection bias in default models. As a result, banks can achieve a better calibration of default probabilities. In Chapter 4, we provide an assessment of approaches to estimate prepayment and default across multiple periods. The analysis of alternative approaches as well as prepayment selection in default models could help banks to more accurately assess credit risk over the lifetime of mortgages and better implement the latest banking regulations (IFRS 9 and US GAAP).

For policymakers, the studies in this thesis provide prudential suggestions about the guarantee policy, loan loss provisioning, and capital adequacy requirement. As seen in Chapter 2, the adoption of the guarantee may have led to stronger growth in residential mortgage lending. Therefore, sound regulation is required to restrict the moral hazard problem associated with a wholesale funding guarantee. Further, Chapter 3 suggests that regulators should be aware that omitting the selection effect of prepayment may result in inadequate loan loss provisioning or capital requirements for high-prepayment-risk segments, especially during economic upturns. Chapter 4 implies for regulators that along with guidelines for banks to comply with the latest banking regulations, regulators should also assess and validate methodologies that banks may apply.

In terms of the banking system, the thesis provides insights to improve the efficiency and resilience of financial system. In particular, Chapter 2 shows that the guarantee scheme did not incur excessive risk for banks. This result supports the implementation of the policy in terms of impact and efficiency to enhance the confidence of investors and maintain the resilience of banks during the crisis. In addition, the study on prepayment selection in Chapter 3 suggests that high defaults in downturns are mainly caused by borrowers who had low prepayment risk due to high LTV ratio. This is a result from tightening lending standards by banks, making refinancing harder for borrowers. If the system can provide support for refinancing opportunities and help consumers to reduce financial payments in the crisis time, there may be a chance to reduce default rates.

Overall, all three studies in this thesis provide new insights and original findings to both researchers and practitioners dealing with credit markets. As a result, it makes significant contributions to improve the efficiency and resilience of the banking system.

5.4 Opportunities for future work

The thesis offers some suggestions on future work. Future research on government guarantees should focus on the ways in which banks can respond quickly to the removal of explicit government guarantees to ensure that a level playing field can be restored in a manner that is least disruptive on credit supply and ultimately the real economy.

Future research on prepayment selection may investigate the impact of prepayment on loan pricing as the choice to prepay by borrowers can alter cash flow structures of mortgages as well as cause a loss of potential incomes for banks.

Future research on multi-period default forecasts may focus on term structure of default over borrower age. The age effect may be interacted with the effect of the macroeconomy and the direction of risk changes may be analysed when a loan is getting older. Answering these questions may help banks to further improve default predictions in the long-run.

Appendix

This section describes the modelling framework of a multinomial Logit model, which is mentioned in Section 3.4.2.

Multinomial Logit model

The Multinomial Logit model estimates multiple possible outcomes and uses the same set of variables to explain all outcomes. In the mortgage context, prepayment and default are considered as two competing risks (with the reference category being non-prepayment/non-default).

The intuition of MNL is that a borrower can have a "choice" of prepayment or default or neither depending on a utility that he or she receives for each option. Assume a utility of a borrower i from a choice s is a linear combination of observed borrower and loan specific characteristics, x_{it} and random error $\varepsilon_{it,s}$ as following:

$$U_{it,s} = \beta_s x_{it} + \varepsilon_{it,s} \tag{21}$$

$\varepsilon_{it,s}$ are independent error terms following a Type I (Gumbel) extreme value distribution with cumulative density function $F(\varepsilon_{it,s}) = exp\left(-exp(-\varepsilon_{it,s})\right)$.

In Eq (21), $U_{it,s}$ is the utility of a borrower i at time t with a choice s. All choices are explained by the same vector of observed borrower and loan specific characteristics, x_{it} with a corresponding parameter β_s.

The status of choice of a borrower may be expressed as:

$$S_{it} = \begin{cases} 2 & \text{if prepayment} \\ 1 & \text{if default} \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

The dependent variable, S_{it} is equal to two if a loan is prepaid, equal to one if a loan is in default and zero otherwise.

Consider continuing borrowers ($S_{it} = 0$) are the reference group. A borrower chooses the prepayment option when $U_{it,2} > U_{it,0}$ as:

$$U_{it,2} - U_{it,0} = (\beta_2 x_{it} + \varepsilon_{it,2}) - (\beta_0 x_{it} + \varepsilon_{it,0}) = (\beta_2 - \beta_0)x_{it} + (\varepsilon_{it,2} - \varepsilon_{it,0}) > 0 \tag{23}$$

Similarly, a borrower chooses the default option when $U_{it,1} > U_{it,0}$ as:

$$U_{it,1} - U_{it,0} = (\beta_1 x_{it} + \varepsilon_{it,1}) - (\beta_0 x_{it} + \varepsilon_{it,0}) = (\beta_1 - \beta_0)x_{it} + (\varepsilon_{it,1} - \varepsilon_{it,0}) > 0 \tag{24}$$

If we define $U^*_{it,2|0} = U_{it,2} - U_{it,0}$, $U^*_{it,1|0} = U_{it,1} - U_{it,0}$, $\beta_{2|0} = \beta_2 - \beta_0$, $\beta_{1|0} = \beta_1 - \beta_0$, $\varepsilon^*_{it,2} = \varepsilon_{it,2} - \varepsilon_{it,0}$, and $\varepsilon^*_{it,1} = \varepsilon_{it,1} - \varepsilon_{it,0}$, Eq (23) and Eq (24) become:

$$U^*_{it,2|0} = \beta_{2|0} x_{it} + \varepsilon^*_{it,2} \tag{25}$$

$$U^*_{it,1|0} = \beta_{1|0} x_{it} + \varepsilon^*_{it,1} \tag{26}$$

Eq (25) and Eq (26) are two independent equations as a random error $\varepsilon_{it,s}$ is assumed to be normal distribution.

We estimate the model parameters by maximizing the log likelihood:

$$lnL = \sum_{i=1}^{I} \sum_{t=1}^{T} lnP(S_{it} = s, \beta_s) \tag{27}$$

The prepayment probabilities and default probabilities can be estimated using the MNL model as follows:

Prepayment: $$\widehat{Pr}(S_{it} = 2) = \frac{\exp(\widehat{\beta}_2 x_{it})}{1+\exp(\widehat{\beta}_1 x_{it})+\exp(\widehat{\beta}_2 x_{it})} \tag{28}$$

Default: $$\widehat{Pr}(S_{it} = 1) = \frac{\exp(\widehat{\beta}_1 x_{it})}{1+\exp(\widehat{\beta}_1 x_{it})+\exp(\widehat{\beta}_2 x_{it})} \tag{29}$$

Note Eq (28) and Eq (29) are the estimated unconditional probabilities of each option for the population. The sum of probabilities of all outcomes (prepayment, default and continuing by borrowers) is equal to one. The implied default probabilities are not calibrated as due to our selection mechanism, default is only observed for non-prepaid borrowers. Therefore, as first in kind, we compute the conditional PD given a borrower is non-prepaid as:

$$\widehat{Pr}(S_{it} = 1 | S_{it} \neq 2) = \frac{\widehat{Pr}(S_{it}=1)}{(1-\widehat{Pr}(S_{it}=2))} \tag{30}$$

Eq (30) is an adjustment to convert predicted PD for the population to the level of predicted PD for non-prepaid borrowers (i.e., the observed sub-sample).

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