Financial Barriers, Regulations and Innovations in Mortgage Markets

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Certificate of authorship

I, Thi Thanh Chung Mai, declare that this thesis, entitled "Financial Barriers, Regulations and Innovations in Mortgage Markets", is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in Finance in the Business School at the University of Technology Sydney.

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

This document has not been submitted for qualifications at any other academic institution.

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To my dear parents

Ba Đông and Mẹ Nhung

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Preface

Chapters 2 to 4 in this thesis have each been developed into a working paper with Prof. Harald (Harry) Scheule. The three papers are titled:

1. Benchmarking measures of systematic mortgage risk for capital frameworks of Government-Sponsored Enterprises
2. Personalized contracts for financial resilience in mortgage lending, *R&R Journal of Banking and Finance*
3. Unravelling the dynamic effects of conforming loan limits on house prices

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List of Abbreviations

AC	Asset correlation
AFRM	Age-adjusted fixed-rate mortgage
ARM	Adjustable-rate mortgage
CLL	Conforming loan limit
CPD	Conditional probability of default
DFRM	Deferred fixed-rate mortgage
DPFRM	Deferred principal-only fixed-rate mortgage
DTI	Debt-to-income
DTM	Double-trigger model
FHFA	Federal Housing Finance Agency
FRM	Fixed-rate mortgage
GFC	Global financial crisis
GSE	Government-sponsored enterprise
HMDA	Home Mortgage Disclosure Act
HPI	House Price Index
IFRM	Income-adjusted fixed-rate mortgage
IV	Instrument variable
LGD	Loss given default
LTI	Loan-to-income
LTV	Loan-to-value
MBS	Mortgage-back security
MNL	Multinomial logit
PD	Probability of default
PP	Probability of payoff
ROC	Return on capital
SB	Scheduled balance
SP	Scheduled payment
TTC	Through-to-cycle
UL	Unexpected loss
US	United States of America
WCDR	Worst-case default rate

Abstract

Financial barriers are at the heart of the challenges faced in mortgage markets. Efforts to alleviate financial barriers are crucial for fostering inclusive access to mortgage markets. This thesis encompasses three studies that investigate the financial barriers experienced by various market participants and propose innovative solutions to mitigate these obstacles.

The first study examines the establishment of a risk-based capital framework for Government-Sponsored Enterprises (GSEs) required by Federal Housing Finance Agency by 2025. We propose a unified framework that integrates observed and unobserved systematic risk factors to assess the level of systematic risk. We further conduct a detailed analysis of the level and cyclicality of capital requirements for three distinct models under this framework, which vary in their degree of control over the observed factor. Utilizing the unified framework results in a smaller asset correlation—a capital constituent, mitigates the procyclicality in capital requirement, lowers capital ratios, and captures more sensitivity of mortgage rate to systematic risk. In the nutshell, GSEs' capital charges under the unified framework stands at 164 billion, which is significantly lower than the current requirement of 312 billion but aligns with industry expectations. Our findings also reveal heterogeneity in the exposure to systematic risk for lender types, recourse laws, and states. These findings contribute to the establishment of more precise capital requirements and loan pricing strategies.

The second study explores the new contracts to alleviate borrowers' financial constraints in accessing credit. We design two novel ex-ante personalized contracts based on borrowers' income expectations and risk profiles over loan age. We benchmark these contracts to 30-year fixed-rate mortgage contracts (FRMs) and ex-post contracts where cashflows are deferred following the financial constraints of borrowers. The proposed contract innovations reduce illiquidity but increase leverage. The combined effects reduce the probability of default, systematic risk, and regulatory capital. Due to the risk reduction, lenders can increase the return on regulatory capital by 10 percent, or alternatively, borrowers may benefit from credit spreads that are 17 basis points lower. Overall, our contracts enhance financial system resilience and increase competitiveness in the mortgage market.

In the third study, we investigate the relationship of conforming loan limits (CLL)—

GSEs' securitization rule—and house price regarding the moderating effects of lender and borrower constraints. CLLs are asymmetrically linked to house prices as they stay unchanged when house prices decrease or remain flat but are raised when house prices increase. We analyze whether this asymmetry introduces a regulatory bias that affects house prices and artificially inflates housing prices. We find a positive impact in the year prior to 2017 when CLL was not adjusted downwards to align with declining house prices, but we do not find an impact when CLL growth aligns with house price growth. Moreover, this effect exhibits heterogeneity among various lenders and borrowers, with more pronounced effects observed among market participants who face fewer constraints. This includes bank lenders who face less constraint in accessing funding sources, borrowers in non-recourse states who are more willing to seek additional credit due to having lower personal liabilities in a default event, and borrowers who are less financially constrained. Our findings call for a tight alignment of CLL and house price changes to avoid housing market distortions. Existing zero growth floors for CLL should be dropped.

In summary, this thesis contributes to our understanding of financial barriers encountered by the mortgage market's participants and how to mitigate them to strengthen financial resilience and market competitiveness as well as create a more inclusive and equitable economy.

Chapter 1 : Introduction

1.1 Research background and motivation

Household debt plays a critical role in the economy, including stimulating consumption, encouraging investment, and driving economic growth. The US, Macao SAR, Hong Kong SAR, Japan, China, and a number of OECD countries are on the list of countries with the highest total household debt to GDP ratios. Mortgages occupy the largest component of household debt. The outstanding US mortgage debt had reached $19.3 trillion by the end of 2022, representing 66.4 percent of the nominal GDP.[1] Mortgages also contribute at least 45 percent of the loan portfolio held by commercial banks.[2]

There is also a strong interconnectedness between mortgage and other markets, such as housing and financial markets. Changes in one market can exert far-reaching effects on others. Vivid examples include the global financial crisis (GFC) induced by the mortgage foreclosure crisis in 2008–2009, creating strong downward pressures on house and equity prices; the implementation of several stimulus programs for homeowners and mortgage lenders during the COVID-19 pandemic to prevent a wave of foreclosures, causing economic uncertainties and increasing inflation pressure. For these reasons, mortgage finance research has drawn considerable attention in recent decades.

Mortgage research literature covers a wide range of topics. The earliest mortgage studies focus on exploring factors that drive mortgage defaults and establishing credit risk models. The selection bias in mortgage risk among default, refinancing, and prepayment is also discussed in this area. There is still a growing interest in this topic, as many techniques have been discussed to reach a consensus on the most compatible models for estimating and forecasting mortgage

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[1] Source: ceicdata.com

[2] Data from the Fed indicates that total real estate loans are $4.8 trillion and the total loan portfolio is $10.8 trillion by Feb 2022 (see, https://www.federalreserve.gov/releases/h8/current/default.htm)

risk. This topic is further expanded in the literature on mortgage pricing. Another branch of mortgage research concerns mortgage choices and designs. Studies in this field primarily discuss borrowers' choices of optimal mortgage types and designs conditioned on their financial constraints and aim to achieve macroeconomic stability. Several studies published since the GFC also shifted their focus to regulation and consumer protection in the mortgage market. This is motivated by various regulations for mortgage markets due to the concern of weakened resilience in the financial system caused by mortgage default waves. A sizable portion of mortgage research focuses on mortgage origination and securitization due to its importance in providing market liquidity. Studies related to this topic provide insight into the influential role of securitization channels micro- and macro-prudentially. Finally, the most recent studies have examined the technology adoption trend in mortgage markets, as these technology-agile lenders cause major disruptions in the mortgage market in terms of escalating competition and credit distribution.

Regardless of the various topics, the core idea of mortgage research focuses on investigating the financial barriers of lenders in supplying credit and borrowers in obtaining credit and their impacts and exploring solutions to relax these barriers and achieve more efficient and inclusive markets. Despite the increasing number of studies, the understanding of financial constraints in the mortgage market remains puzzling and requires further research to drive innovations in mortgage markets.

1.1.1 Mortgage risk and pricing

The majority of mortgage research focuses on the concepts and techniques of credit risk models. One of the earliest studies on residential mortgages was conducted by Herzog and Earley (1970). They found that such characteristics as loan-to-value (LTV) ratio, debt-to-income (DTI) ratio, and term-to-maturity contribute to fluctuations in mortgage risk over time. This pioneer evidence lays the foundation for the double-trigger mortgage default theory, in which mortgage defaults likely result from a combination of negative equity and illiquidity. This double-trigger model (DTM) outweighs the frictionless option model (Epperson et al., 1985), in which mortgage default is explained as a consequence of negative equity only. Foote and Willen

(2018) provided a thorough review of these mortgage default theories. Several studies provide empirical evidence supporting the DTM in the literature, such as Campbell and Cocco (2015), Corradin (2014), Gerardi et al. (2018), Laufer (2018), and Schelkle (2018).

The estimations for the hazard models have varied across regression methods and identification. The traditional methods are ordinary least squares and logistic models,[3] which later developed into more complex methods to address competing risks: Bhattacharya et al. (2019) employed a Bayesian competing risk proportional hazards model, Calabrese and Crook (2020) introduced a spatial discrete survival model, and Djeundje and Crook (2019) used the discrete-time survival models with B-splines. Regarding identification, the point-in-time model, with the inclusion of macroeconomic variables, allows for the capture of more default variations than the through-to-cycle model, which is completely abstract from the state of the overall economy. The combination of the lifecycle model and the forward model also proves to be a better model for predicting default probabilities (Luong & Scheule, 2022).

Mayer et al. (2009) and Mian and Sufi (2009) argued that mortgage defaults and delinquencies normally occur among subprime or near-prime borrowers, which later formed the mortgage default crisis. In contrast, Adelino et al. (2016) found that more middle-income, high-income, and prime borrowers fell into delinquency during the crisis. Corbae and Quintin (2015) provided additional evidence that high-leverage loans prior to the crisis contributed to over 60 percent of the rise in foreclosure rates. Ghent and Kudlyak (2011) found that recourse law (i.e., deficiency judgment) helps reduce the probability of default.

Most studies focus on estimating the total risk (i.e., probability of default) or idiosyncratic factors but are limited to examining the default variations driven by systematic risk factors or investigating mortgage exposure to systematic risks. This is partly due to the current industry practice, in which a single value of asset correlation (i.e., the systematic risk level for residential mortgages) is used to calculate the capital requirement (Calem & Follain, 2003). Cowan and Cowan (2004), Jiménez and Mencía (2009), and Lee, Rösch, and Scheule

[3] See Chapter 6 and Chapter 7 in Baesens, Rosch, & Scheule (2016) for detailed explanations.

(2021) provided empirical evidence of the heterogeneity in default correlation across different mortgages.

1.1.2 Mortgage choices and designs

Campbell and Cocco (2003) were among the first to discuss optimal mortgage choices for households. They argued that an adjustable-rate mortgage (ARM) is generally more attractive than a fixed-rate mortgage (FRM) regarding borrowing constraints and income risk. The mortgage choice can also be influenced by the term structure of interest rate (Koijen et al., 2009), the rational forecasts of ARM rates (Badarinza et al., 2018), or the nonprice supplier effects (Foà et al., 2019).

Recent studies have proposed various mortgage designs with the aim of achieving macroeconomic resilience, such as Campbell et al. (2021), Greenwald et al. (2021), and Guren et al. (2021). However, these studies only established a theoretical framework and relied on the calibration of the simulated data. Although the model parameters could align with observed average values, the lack of examination of the data at micro levels is a limitation.

1.1.3 Regulations in the mortgage market

Due to the aftermath of the GFC, the mortgage sector has become heavily regulated. This has initiated multiple research discussions on the effectiveness of the regulation in the mortgage market. Agarwal et al. (2012) investigated the Community Reinvestment Act enacted in 1977 in the US, encouraging financial institutions to meet the credit needs of local communities. They found that adherence to the Act results in riskier lending. Following the GFC, the US government implemented two programs, the Home Affordable Refinancing Program and the Home Affordable Modification Program, to curb the foreclosure waves. Studies by Agarwal et al. (2017a) and Agarwal et al. (2023) indicated that these programs help reduce financial constraints for borrowers and curtail delinquency. During the COVID pandemic, the Coronavirus Aid, Relief, and Economic Security (CARES) Act allowed borrowers to delay their mortgage repayments (i.e., forbearance). The timely implementation of this policy effectively prevented the surge of foreclosure and maintained the stability of the financial system (Gerardi et al., 2022; Kim et al., 2022).

1.1.4 Innovations in the mortgage market

Over the last decade, mortgage lenders have shifted from traditional banks to nonbank lenders. These new players have greatly blended into mortgage markets and earned a higher market share. In 2020, more than 70 percent of mortgage originations are issued by nonbank lenders.[4] The most dramatic growth is among fintech lenders. With these eruptions, the research surrounding these new players has been brought to the spotlight. Buchak et al. (2018) stated that the success of shadow banks, including fintech lenders, comes from a regulatory advantage. This argument is consistent with Tang's (2019) study. Other explanations for the emergence of nonbank lending are linked to the Fed's monetary tightening campaign (Evans & Robertson, 2018) or secondary market innovations such as the introduction of eMortgage and securitization through GSEs (Jiang, 2023).

Several recent studies have explored the reasons for the growth of fintech lenders. Fuster et al. (2019) argued that a shorter processing time is the main reason that fintech lenders can win their share of the market share. The increasing fintech share also results from the decline in bank lending (Gopal & Schnabl, 2022), their advantage in processing hard information (Balyuk et al, 2020), or their geographical diversification strategy enabled through technological adoption (Basten & Ongena, 2019). Further explanations for the popularity of fintech lenders is how their lending strategy may target areas which previously experienced high application denial rates by non-fintech lenders (Jagtiani et al., 2021), initially lending to low-credit-score borrowers (Bao & Huang, 2021; Di Maggio & Yao, 2021; Dolson & Jagtiani, 2021), or offering smaller rate premiums on unconventional loans (Bartlett et al., 2022).

As a result of rapid technological adoption, nonbank lenders have undergone significant

[4] https://www.wsj.com/articles/nonbank-lenders-are-dominating-the-mortgage-market-11624367460

evolution and emerged as a crucial force in mortgage markets. Considering this development, one of the primary objectives of this thesis is to conduct subsample analyses encompassing both banks and nonbanks. By doing so, a comprehensive understanding of the distinct characteristics and roles of these lenders within the market can be obtained, offering a clearer picture of the overall landscape.

1.1.5 Motivations

Government-sponsored enterprises (GSEs) have played a significant role in shaping the mortgage market structure and providing stable liquidity for mortgage sectors. However, their resilience still relies on the conservatorship of the Federal Housing Federal Association (FHFA), and there is growing concern about requiring them to maintain a certain level of capital requirements, ensuring a sound operation manner. This process has started, but the regulatory framework currently follows a standard approach that fails to account for the risk variations. Academic and industry experts have also engaged in discussions regarding the capital rule, highlighting the cyclicality of capital requirements and the undue burden imposed by high capital charges. This might inhibit lending and impede the sustainability of homeownership growth. The transition to a risk-based capital framework is essential to enhance the current situation. In fact, FHFA has mandated that GSEs develop their own risk-based capital models by 2025. Systematic risk plays a pivotal role in capital requirements, and the first study in my thesis focuses on constructing a comprehensive framework that integrates both observed and unobserved risk factors. The framework is designed to accurately estimate the level of systematic risk, which can be effectively utilized within the GSE capital framework.

Regarding mortgage contracts, while there have been some innovations in the market and research, there is a general lack of empirical evidence on their effectiveness or applicability. Many studies provide a theoretical framework and do not consider the specific conditions of borrowers. The importance of the second research is of particular importance currently due to the impact of the recent COVID crisis on housing affordability, the fluctuations of interest rates, and heated inflation in many economies around the world. A change in mortgage contracts that can reduce constraints in borrower lending, leading to a reduction in default risk, would be of significant benefit to lenders, borrowers, and related financial institutions.

This leads to the rationale behind our third paper, which concerns the impact of mortgage-related interventions spilling over other sectors. Many industries are connected and linked, where regulatory changes in one can influence the other. When we consider the breadth and importance of mortgages in the general economy, any changes to mortgages can have a flow-on effect on other related industries and parties. One such related industry would be the overall housing market. To date, many studies have not investigated heterogeneity effects from government interventions, and as a result, there is a lack of research into the moderating effects of these regulatory measures on different lenders and borrower types. Given the growing appetite for government intervention and action in the housing market, research into how measures can be safely applied while reducing undesirable events is necessary.

1.2 Research scope and contributions

This thesis aims to elaborate our understanding of the financial barriers faced by market players and to propose various solutions to mitigate the constraints. The findings could carry important implications for industry practices and prudential policies, helping to develop more resilient and inclusive mortgage markets.

The first study (Chapter 2) focuses on the regulatory capital constraint faced by the GSEs. Developing a risk-based capital framework is necessary to assess GSEs' systematic risk and capital requirements. We establish a comprehensive framework that unifies both observed and unobserved systematic risk factors under the argument that both factors interdependently explain the systematic variations in mortgage portfolios. While the current Basel framework employs a single latent risk factor to estimate the systematic risk level (i.e., asset correlation [AC]), the estimation of AC from the two-factor risk model is conditioned on the incorporation of the observed factor, which is captured by macroeconomic conditions. We evaluate three probability of default (PD) models based on the unified framework but differ in their levels of incorporating the observed factor. The more proper incorporation of the observed factor could result in a higher peak-to-trough average PD variations—source of procyclicality in capital requirements. However, this could be counterbalanced by the decrease in AC as we find that the higher the level of observed factor is controlled, the lower AC estimates become. These offsetting effects not only reduce the cyclicality of capital requirements but also lower the associated capital charges. We also uncover that a stronger sensitivity is found in mortgage rates to the capital charges calculated from the unified framework than in the regulatory benchmark. This indicates a better alignment between our proposed framework and the lenders' risk management practices. Finally, systematic risk varies across types of lenders, types of recourse laws, and states. Specifically, loans originating from nonbanks, located in nonrecourse states and/or California, carry a higher exposure to systematic risk. Through examining different models in terms of procyclicality, capital requirements, and the impact on pricing, our findings suggest that a more comprehensive framework allows for uncovering the systematic shocks that would help GSEs to develop more accurate portfolio risk models, enhance their risk management abilities, and achieve better pricing schemes.

The second study (Chapter 3) focuses on borrower constraints and explores how mortgage contracts could be designed to enable more borrowers to have credit access and concurrently mitigate systematic risk. Building on the findings of Chapter 2, we confirm that the income (i.e., liquidity) constraint plays a more critical role in driving mortgage default. Therefore, we introduce two novel ex-ante personalized contracts based on borrowers' income expectations (i.e., Income-adjusted FRM [IFRM] contract) and risk profiles over loan age (i.e., Age-adjusted FRM [AFRM] contract). Unlike FRM, which requires borrowers to make annuities, IFRM's repayment pattern is increasing over time to reflect greater serviceability in later years of a loan due to higher income, and AFRM's portrays a reversed hump shape directly offsetting loan age or lifecycle-related risks. The proposed contract innovations reduce illiquidity but increase leverage due to payment delays. Using a counterfactual analysis, we test our new designs' efficacies by comparing them against the 30-year FRMs and ex-post contracts, where cashflows are deferred following the financial constraints of borrowers. Compared to benchmark loans, our results show that two new designs help achieve a lower probability of default and systematic risk, hence curtailing regulatory capital. This indicates an enhancement in financial system resilience if new contracts are adopted. In terms of economic meaning, lenders can increase the return on regulatory capital by 10 percent due to risk reduction. Alternatively, lenders can transfer the benefit to borrowers by offering credit spreads that are 17 basis points lower. We argue that the new contracts boost competitiveness in mortgage markets and perhaps bolster the national economy. Given recent significant fluctuations in interest rates and inflation rates, it is anticipated that household incomes will also vary accordingly. Our proposed contracts aim to effectively counterbalance these exposures and could be potential solutions to mitigate these risks.

The third study (Chapter 4) examines the impact of adjusting the CLL level on the housing market regarding the moderating effects of lender and borrower constraints. The CLL is the maximum loan amount eligible for securitization through Fannie Mae or Freddie Mac, which is supposed to reflect national house price growth. However, regulators (i.e., the FHFA) tend to keep CLL unchanged or increasing regardless of the housing market trend, raising concerns about inflating house prices. After controlling for endogeneity, we documented a positive effect of regulatory bias on local house prices. It is argued that the tendency of CLL increase allows an expansion of credit supply, stimulating housing demand and ultimately driving house prices. Interestingly, this effect is significant when CLL diverges from the national house pricing trend (i.e., before 2017) but insignificant when CLL perfectly follows housing market fluctuations (from 2017 to 2021). We also find that lender and borrower constraints influence this effect. Less constrained market participants are more likely to react to policy interventions, leading to a stronger impact on house prices. These include nonbank lenders, borrowers living in nonrecourse states, and less financially constrained borrowers. Our findings suggest that regulators should follow the market signal and consider the heterogeneous moderating effects from different market participants when setting CLL to avoid housing price distortions and economic inequality.

1.3 Thesis outline

This thesis is organized into five chapters. This introductory chapter presents the research background on mortgage markets, lenders, and borrower barriers, providing the motivations and overview of the three subsequent studies. **Chapter 2** evaluates alternative risk-based frameworks that GSEs could consider choosing going forward and derives implication for mortgage pricing. **Chapter 3** introduces two novel ex-ante contracts alleviating borrowers' income constraints and analyses their impacts on enhancing market resilience and competitiveness. **Chapter 4** investigates how regulatory bias induced by relative CLL changes affects local house prices and the moderating effects of lender and borrower constraints. **Chapter 5** summarizes the conclusions and suggests future research directions.

Chapter 2 : Benchmarking measures of systematic mortgage risk for capital frameworks of Government-Sponsored Enterprises

2.1 Introduction

Government-Sponsored Enterprises (GSEs) such as Fannie Mae and Freddie Mac play an essential role in providing liquidity for mortgage markets and maintaining a steady flow of capital into the housing market. The statistics from the Home Mortgage Disclosure Act data indicate that nonbanks sold up to 97 percent of their 1–4 family loan portfolios while banks sold approximately 50 percent (FDIC, 2019). This role also means that GSEs suffered significant capital losses during the GFC and required rescue packages from the government, resulting in an extra burden for taxpayers.[5]

Subsequent to these events, it is imperative for GSEs to maintain a robust capital framework to ensure their operational resilience during crisis periods. GSEs are currently required to utilize the standard approach by looking up the risk weights from tables using the mark-to-market loan-to-value ratios prescribed by the regulator FHFA. However, as part of their ongoing transition, GSEs are required to adopt the advanced approach, necessitating the integration of internal models for capital calculation purposes by January 1st, 2025. This transition underscores the importance for GSEs to develop a comprehensive risk-based capital framework.

Measuring systematic risk is critical for providing adequate capital levels to safeguard GSEs. We propose a two-factor risk model incorporating both observed and unobserved

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[5] The Emergency Economic Stabilization Act provided $475 billion in bailout relief through the Troubled Asset Relief Program. Between January 2009-March 2010 the Federal Reserve system purchased more than $1.2 trillion of mortgage securities and debts from GSE's.

systematic risk factors as the potential capital framework for GSEs. The observed factor drives the average probability of default (PD), while the unobserved factor determines the asset correlation (AC) reflecting the intercorrelation among borrowers' asset value.[6] This framework may consider but is not required to comply with Basel's internal ratings-based approach. The model features can be chosen by model builders based on their rating philosophies. As more macroeconomic (i.e., both local and nationwide) conditions are incorporated into the PD models, the degree of observed systematic risk increases and replaces the role of unobserved systematic risk. Due to some discussions on leveling the playing field, we compare our economic capital ratio to the regulatory capital ratios implied by the Basel framework.

Our paper makes several contributions to literature. First, our study develops a unified framework incorporating both observed and unobserved systematic risk factors, arguing that both factors interdependently explain the systematic variations in mortgage portfolios. Unlike the current Basel framework, which utilizes a single latent risk factor to estimate AC as the systematic risk, the two-factor risk model producing the estimates for AC is conditioned on the inclusion of observed systematic risk. Examining three models with the increasing level of observed factor, we find that AC exhibits a decreasing pattern.[7] Interestingly, the exposure to the observed factor (i.e., Beta) could possibly serve as a measure of procyclicality in mortgages. Whilst we focus on GSE mortgage loans, the framework may be generalized to other exposure classes and non-GSE applications.

Second, we provide a detailed comparison in terms of levels and cyclicality of capital requirements between Basel and our unified frameworks. We show that fully incorporating

[6] The individual probability of default reflects the effects of both idiosyncratic and observed systematic risk factors. When averaging PD across a large portfolio, idiosyncratic risk is cancelled out. Hence, average PD captures the effect of observed systematic risk factors. The average PD is also a component in the equation for calculating capital requirements according to the Basel regulation. AC is the second component in the capital equation and is driven by the unobserved factor.

[7] The quick descriptions of three models are: The Origination Model only captures the idiosyncratic risk, the +Dynamic model additionally captures the local systematic risk, and the +Macro model further controls the nationwide systematic risk. The setups of three models are described in the empirical framework section 2.3.

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macroeconomic conditions widen the peak-to-trough variations in average PD, which potentially increases the procyclicality in worst-case default rate and capital ratios. However, this can be mitigated by utilizing the unified framework as the capital constituent—AC—is downward-adjusted conditioned on the increase in the level of observed factor. We uncover that the Max-Min difference in worst-case default rate (i.e., the measure of cyclicality) drops from 6.7 percent under Basel to 2.5 percent under the unified framework. Additionally, the capital ratio under the unified framework is notably lower than that under Basel, with figures of 2 percent and 6.7 percent respectively. Given the combined total assets of Fannie Mae and Freddie Mac are 8.2 trillion, the economic stands at 131 to 164 billion. This number aligns intriguingly with the industry expectation and the recent GSE stress test outcomes. It is also worth noting that the capital level could potentially decrease further when average PD increases due to the comprehensive inclusion of macroeconomic conditions. This is because higher PDs result in higher loan loss provisions which further reduce the capital level.

Third, we find that using the outcomes from the two-factor risk model framework results in a stronger sensitivity in mortgage rates than the Basel benchmark. We calculate the unexpected loss as compensation for exposure to systematic risk by using the mean PD and estimated AC. The findings from regressing mortgage rates on unexpected losses indicate a higher sensitivity if more macroeconomic conditions are incorporated under the two-factor risk model framework. This implies an alignment between the proposed framework and the lenders' internal risk management practices, which helps improve the pricing scheme relative to systematic risk for lenders and strengthens the well-regulated and resilient system.

Finally, we provide empirical evidence exploring the heterogeneous exposures to systematic risk factors for various groups of loans based on lender types, recourse types, and states. Specifically, loans originated by nonbank lenders, located in nonrecourse states and/or California tend to carry higher systematic risk levels. These findings are aligned with our priors as these loans are perceived to be riskier than their counterparts and suggest that using different exposures of systematic risk in calculating regulatory capital for different mortgages could be more reasonable and efficient.

Our findings carry important implications for any future development into an internal model-based framework. Regulators may design their framework as a two-factor risk model to incentivize the measurement, management, and optimization of systematic risk. Specifically, bank regulators do not distinguish between the level of systematic risk (a flat AC of 15 percent is required for mortgage loans for Basel-regulated banks) and whether risk measures such as default probabilities reflect beta through (limited) point-in-time ratings. This means that while loan criteria can reduce risk to a certain degree, this blanket approach can mean some loans may be riskier than expected, while other loans may be denied despite being within risk tolerance. Utilizing a two-factor risk model can assist GSEs to better price acceptable loans while maintaining a consistent level of risk.

The flow-on effects of greater risk utilization will also spur lenders to improve their risk models to retain market access to securitization. A more accurate model to assess default risk, GSEs incentivize lenders to better identify borrowers who are more likely to default on their mortgages. This allows lenders to adjust their lending standards and target their loans towards borrowers with lower default risk. As a result, lenders may be more selective in lending to riskier borrowers while providing more opportunities for creditworthy borrowers to access mortgage securitization. This change in lending standards can in turn help mitigate the adverse selection problem in mortgage securitization.

The study also suggests that adopting a more comprehensive risk-based capital framework can lead to lower capital requirements for lenders. This is because the more risk-sensitive models capture higher levels of default risk, resulting in higher expected losses. As a result, the capital requirements decrease, allowing lenders to allocate more capital towards lending activities. Lower capital requirements can incentivize lenders to increase their lending activities, potentially leading to more overall lending in the mortgage market. This can help stimulate the housing market and promote access to mortgage credit for borrowers.

Similar economic principles apply to capital operations of GSEs and commercial banks. GSE capital combines traditional government (i.e., shareholder) funds with credit risk transfer (Finkelstein et al., 2018; Layton, 2020a). From the gross capital required, a substantial proportion of their credit risks is provided by financial institutions such as reinsurance companies, which involves the payment of insurance premiums. The remaining capital is provided by the government. Additional capital can be either provided by additional insurance coverage or additional injections of capital from the government. Insurance solutions are less common for commercial banks.

This chapter proceeds as follows. The following section reviews the relative empirical findings in the literature, including the involvement and discussion of the Enterprises Regulatory Capital Framework. Section 2.3 establishes a framework for estimating mean PD and AC and pricing systematic risk. Section 2.4 describes the data and constructions of variables. Section 2.5 presents and discusses the results of empirical tests, including payoff probability models, default probability models, measuring systematic risk levels, the impact of systematic risk levels on mortgage rates, and the robustness tests. Finally, we deliberate on the industry impacts in Section 2.6.

2.2 Literature review

Mortgage models are large in number and granular. The realization of systematic risk is key to providing capital to safeguard GSEs from the realization of systematic loss. The literature has analyzed both observed and unobserved systematic risk factors in isolation. Most papers examine the directional impact of factors (stream 1) but do not provide methods to measure the level of systematic risk (stream 2). We describe the literature on systematic price measures in more detail below. [8]

2.2.1 Observed systematic risk factors

Most research papers include macroeconomic variables as observed systematic factors in PD models and predict mortgage defaults. For instance, Elul et al. (2010) examined the effects of unemployment on mortgage default probabilities; Amromin and Paulson (2009) confirmed

[8] We also summarize previous literature on the measurement of systematic risk in the Appendix 2.A

the role of real estate prices as an essential risk driver; Calabrese and Crook (2020), Goodstein et al. (2017), and Gupta (2019) provided empirical evidence on the positive effect of contagion factors among strategic defaulters.[9] The above studies highlighted the impact of observed systematic factors on default probabilities but did not explicitly estimate the absolute exposure levels of systematic risks.

Hilscher and Wilson (2017) introduced an interesting measure of systematic risk, which is the mean of default probability. With a large portfolio, the mean PD could cancel out the effect of idiosyncratic components and retain systematic variations. This measure is also practical for lenders, as they can implement it easily. We adopt this proxy in our paper, standardize it for interpretation purposes, and capture the fluctuations of observed systematic factors through mean PDs.

2.2.2 Unobserved systematic risk factors

Systematic default risk may also be exposed to unobservable risk factors. The effects of these factors are often referred to as frailty effects. Most of the research in this stream focuses on corporate credit default.[10] Jiménez and Mencía (2009) were among the first to develop a state space model to explain default rates as a function of macroeconomic conditions and frailty risk factors in the Spanish banking system. They documented the effects of macroeconomic factors

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[9] There are more papers on observed systematic risk for corporate loans. Pesaran et al. (2006) show that firms' default probabilities are determined by how strong the connection is between firms and business cycles and their interconnection in business cycles across the globe. Duffie et al. (2007) illustrate the prominent roles of S&P 500 returns and Treasury interest rates in predicting conditional future default probabilities.

[10] Das et al. (2007) and Duffie et al. (2009) analyzed frailty effects for corporate default intensities and hence time clustering. They find that there is a significant gap between default prediction and the measured default intensities modelled by observable macroeconomic covariates such as Treasury bill rate or return of the S&P 500. Even after controlling for extra observable systematic factors, an excess degree of default correlation is still present. The other studies in this line worth considering are Dietsch and Petey (2004), Koopman et al. (2012), and Nickerson and Griffin (2017). In a similar context, Azizpour et al. (2018) pointed out the role of the contagion effect on default clustering after controlling for macroeconomic and frailty factors and suggest that all three factors need to be included to achieve a better forecast of portfolio credit risk. However, they only provide the estimate of variance of default, and do not estimate the specific levels of exposure to different factors.

on expected exposures of default and identified the latent factors that drive default density among different loan sectors. However, they did not explicitly estimate the systematic risk levels.

Exposure to unobserved systematic risk factors is measured by AC. A high value for asset correlation indicates a strong interlink among borrowers, meaning that they are more dependent on the general state of the economy and are more likely to default in adverse conditions. Calem and Follain (2003) suggested the application of a 15 percent asset correlation assumption for mortgages on single-family residences and subsequently found entry into the Basel regulations that are currently globally applied.[11] A recent study by Lee, Rösch, and Scheule (2021) specified that systematic risk is the unexplained variation of default rates and decomposes it into general systematic risk and rating-class-specific systematic risk. Their findings showed that heterogeneity in systematic risk levels across different mortgage classes indicates that medium-risk classes are more exposed to the systematic component. Further, the empirical values were lower than the Basel benchmark parameter of 15 percent for mortgage loans held by regulated banks.

2.2.3 Procyclicality in capital requirements

Procyclicality is the main concern for the regulatory framework of capital requirements. Several studies have been dedicated to either analyzing the cyclicality effect on bank performances/lending decisions or exploring solutions to reduce the cyclicality in capital requirements. Repullo and Suarez (2013) stated that more advanced risk-based capital requirements cause more procyclicality, but disagree on their impact on banks' welfare. Ly and Shimizu (2021) added evidence to this debate by demonstrating that risk-sensitive capital requirement rules could exert a negative impact on bank lending.

Due to these effects, there has been consensus on reducing procyclicality in capital

[11] Hashimoto (2009) estimated the asset correlation for corporate loans. AC is higher at the top and low end of company risk, but lower in the middle range.

requirements. Jokivuolle et al. (2014), based on a theoretical model, suggested that capital requirements should be higher during expansion and lower during recession. Gordy and Howells (2006) examined three policy options (i.e., using the through-to-cycle [TTC] approach in PD models, flattening capital equation, and smoothing capital requirements by counter-cyclical indexing) in terms of their dampening effects on the capital requirement's cyclicality in relation to preserving Basel Pillar 3's market disclosure. They likely favored the third method conditioned on the data available on the state of national credit markets. Other solutions were mentioned in the literature, including using the duration of two business cycles as the optimal look-back period (Lee, Cho, & Yang, 2021), using a forward-looking PD model (Pederzoli & Torricelli, 2005), using risk weights in response to sectoral measures of leverage (Hodbod et al., 2020).

In our study, we scrutinize three stylized PD models utilizing both observed and unobserved systematic risk factors as alternative rating philosophies for GSEs. The inclusion of systematic risk factors varies across the three models and allows us to evaluate how they may contribute to procyclicality in capital requirements for GSEs. The remaining section reports the different risk factors utilized in the literature.

2.2.4 Deterministic drivers of idiosyncratic mortgage risk

The literature on mortgage risk has also explored numerous idiosyncratic factors of default risk. The two most important factors are illiquidity and leverage, which are the core of the DTM.[12] Multiple proxies for illiquidity have been used, such as the debt-to-income (DTI) ratio (Schelkle, 2018), credit card utilization (Elul et al., 2010), loan-to-income ratio (Campbell & Cocco, 2015), and employment status (Gerardi et al., 2018). For leverage, the most popular proxy is the ratio of the outstanding loan balance to the house value (LTV).

[12] Foote and Willen (2018) provided a review on mortgage default models including frictionless option model and double-trigger model. DTM is the most popular one and wildly justified by the empirical evidence.

Information on borrower, loan, collateral, and macroeconomic features are also frequently used to estimate default probability, such as FICO, number of borrowers, loan size, property type, owner's occupancy status, and origination channel. Furthermore, it was found by Ghent and Kudlyak (2011) that borrowers in nonrecourse states are more sensitive to lower house prices and are likelier to default as compared to borrowers in recourse states. This indicates that judicial systems can influence mortgage defaults to some degree. Previous studies also explored the nonlinear relation between borrower age and PD (Debbaut et al., 2016).

2.2.5 Pricing of mortgages

Literature on pricing mortgage spreads is limited for fixed-rate mortgages, as the interest rate is determined at the origination time and remains unchanged throughout the loans' lifetimes. Lenders typically apply similar filtering standards when approving borrowers, resulting in a relatively homogenous borrower pool. As a result, there is limited heterogeneity observed in mortgage interest rates. However, mortgage interest rates between lenders may differ due to different lending policies, risk appetites, and premiums for systematic risk levels. Systematic risk is strongly linked to capital levels and hence the cost of funds, which should be reflected in the mortgage rates.

Rajan et al. (2015) conducted a year-by-year regression and found that the mortgage interest rate has a strong relation with FICO and LTV over time. Antinolfi et al. (2016) described mortgage rates as a function of loan and borrower characteristics such as LTV, FICO, and loan amount. Levitin et al. (2020) found that mortgage rates are less likely to be influenced by loan and borrower characteristics during the housing bubble. These and other studies have shown that loan prices and borrower characteristics are related. Benetton et al. (2021) found a positive relationship between mortgage rates and capital requirements. Justiniano et al. (2022) discovered a disconnect between mortgage interest rates and Treasury yields, which makes mortgages more affordable. Nguyen et al. (2022) documented the positive relation between mortgage spreads and exposure to sea-level rise risk even after controlling for flood insurance. This climate exposure may manifest as a form of systematic risk, and we expect a similar connection between mortgage spreads and our measures of systematic risk. Interestingly, Hurst et al. (2016) found that GSE-eligible mortgage rates do not vary regionally. This finding is consistent with McGowan and Nguyen's (2023) study showing that mortgage lenders prioritize securitization over pricing for regional credit risk.

Relative studies examining the pricing of mortgage-backed securities (MBS) can also be documented to clarify the relationship between mortgage rates and systematic risk. Childs et al. (1996) revealed that the collateral value within a securitization pool is the determinant of the MBS prices and requires higher yield spreads. Boyarchenko et al. (2019) suggested a strong link between the yield spreads on MBS and homeowner funding costs.

The positive relationship between systematic risk levels and risk premium is well documented in the literature for tradeable securities, including stocks (Fama & French, 2015), corporate bonds (Bai et al., 2019), options (Duan & Wei, 2009), futures contracts (Bessembinder, 1992), or CDS (Wang et al., 2013).

2.2.6 Enterprise regulatory capital framework

The Enterprise Regulatory Capital Framework has been developed since 2013 and the FHFA first published the proposed rules for the regulatory capital framework for Fannie Mae and Freddie Mac on 17 July 2018. The aim is to ensure that "each Enterprise operates in a safe and sound manner, that the operations and activities of each enterprise foster liquid, efficient, competitive, and resilient national housing finance markets, and that each enterprise carries out its statutory mission only through activities that are authorized under and consistent with the Safety and Soundness Act and its charter" (Enterprise Regulatory Capital Framework, 2018, p. 8). The introduction of these rules is necessary to facilitate the FHFA to end conservatorships of the Enterprises.

This rule has since been finalized and became effective on February 16th, 2020, with consideration towards mitigating some of the negative effects of aggregate risk-based capital such as procyclicality. Each enterprise is required to maintain the ratio of total capital to risk-weighted assets at a minimum of 8 percent, Tier 1 capital ratio at a minimum of 6 percent, and Common Equity Tier 1 capital ratio at a minimum of 4.5 percent. Separately, they also need to satisfy the leverage ratios of either core capital or Tier 1 capital to adjusted total assets at a minimum of 2.5 percent. We notice that these requirements align with those for US banking organizations and the Federal Home Loan Banks (Enterprise Regulatory Capital Framework, 2020). In 2022, the FHFA further refined the leverage buffer, which was set to be 1.5 percent of the adjusted total assets. This fixed leverage buffer is now set to be dynamic, equal to 50 percent of the stability capital buffer.

The final rule proposes two approaches to determine the risk weights for the assets: standardized and advanced. The former utilizes the FHFA-prescribed lookup grids and risk multipliers determined as the function of mark-to-market loan-to-value ratios (Enterprise Regulatory Capital Framework, 2020, p. 112–116). The LTV ratios should be adjusted by the national, not-seasonally adjusted, expanded-data FHFA House Price Index. Although this regulation could somehow address the cyclicality concern of risk-based capital requirements, the complete effect may be limited as only the national housing market is incorporated. The latter, proposedly effective on January 1st, 2025, is an internal risk-based approach. This requires input from each enterprise's internal models (i.e., the estimated average PD) and could possibly consider incorporating various macroeconomic conditions to reflect more cyclicality in capital requirements.

This GSE capital rule has encountered debate from industry representatives and financial academics that the capital requirements are too high and may harm the liquidity of mortgage markets, as GSEs need to preserve more capital to satisfy the regulations. Layton (2020) argued that GSEs' credit risks are typically lower than equivalent banks regarding the same mortgage portfolio because GSEs can eliminate liquidity and interest rate risk through issuing mortgage-backed securities. Hence, the capital requirements for GSEs should be lower. This view is shared by Golding et al. (2020) who emphasized that the Basel-like framework for GSEs may not be appropriate as they are not banks and urge for the reduction of non-risk-based components in capital requirements. Layton (2023) further reinforced this view by documenting the results from the annual stress test for GSEs in 2022, which the required that capital level should be more than two times lower than the current level.[13] Goodman et al. (2021) demonstrated the cyclicality in the current GSE capital framework and recommend a quick adjustment to prevent potential impairment on lending.

Our study set out to evaluate the different risk-based options that FHFA can adopt for GSEs regarding procyclicality, capital charges, and impact on pricing scheme. The ultimate goal is to contribute to the development of the capital rule to ensure that GSEs can effectively manage risk while maintaining or even growing lending values to support sustainable increases in homeownership for the general public.

2.2.7 Summary

The literature has elucidated that mortgage default clustering has exposure to both observable and unobserved (frailty) systematic risk factors, and these exposures may vary across different subsamples. It could be reasonable to develop a similar implication for GSEs' mortgages, as most mortgages are securitized, and it is through securitization that the GSEs dominate the market.[14] By deriving a unifying framework, we are the first to incorporate both observed and unobserved systematic risk factors at the same interpretational level. We aim to identify the effect of incorporating observed/macroeconomic conditions on procyclicality in capital requirements. The outcomes of this research will guide an ongoing public discussion or provide different options on the potential risk-based framework that GSEs may adopt in 2025.

It is also likely that there is a disparity in systematic risk levels among different mortgage groups, which may require heterogenous capital requirement rules. We aim to exhibit the systematic risk levels for different subsamples based on lender types (banks vs. nonbank

[13] His estimation is around the $120–135 billion range, while the current requirement is $312 billion for both GSEs.

[14] According to the FDIC's (2019) analysis, banks tend to sell around 50% of their 1-4 family mortgage portfolio, while this number is 97% for nonbanks. The share of GSEs in total securitization occupy roughly 60% to 80% based on our own calculations using HDMA data from 2018 to 2021.

lenders), recourse law (recourse vs. nonrecourse), and states (California vs. other states)[15].

The pricing of systematic risk for mortgages has received very little attention. We, therefore, seek the answer to what degree mortgage rate variations can be explained by systematic risk level in our study. As we examined both systematic risk factors concurrently, we observed different pricing sensitivity to each factor across models. To the best of our knowledge, our study is the first to price mortgage spreads against systematic risk levels. Our results have important implications for the pricing of mortgage loans in GSEs going forward.

2.3 Empirical framework

We adopted the Vasicek asymptotic single risk factor model and extended it to a two-factor model for observed and unobserved systematic risk. This model is most common in the discipline and is the basis of the Basel capital framework for banks, where a regulatory value for the loading of systematic risk—AC of 15 percent—is used to calculate capital requirements for all mortgages. We argue that AC could vary according to fluctuations in PD and should be heterogeneous for different groups of mortgages. In this section, we describe the models for estimating PD and AC in detail. Each model reflects different levels of cyclicality and hence exerts different impacts on capital requirements and mortgage pricing.

2.3.1 Estimating average PD

We utilize the Vasicek model or the asymptotic single risk factor model, depicting a latent asset value return process linked to a single systematic risk factor (F) and an idiosyncratic risk factor (U):

[15] A nonrecourse loan only allows lenders to foreclose on borrowers' homes, while a recourse loan allows lenders to pursue other legal action even after the borrowers' homes foreclosure to recover the loss in case of default events. According to state law, there are 12 states allowing for nonrecourse loans: Alaska, Arizona, California, Connecticut, Idaho, Minnesota, North Carolina, North Dakota, Oregon, Texas, Utah, and Washington (see https://www.quickenloans.com/learn/the-difference-between-recourse-and-non-recourse-loans)

$$V_{it} = \sqrt{\omega}F_t + \sqrt{1-\omega}U_{it} \tag{2.1}$$

The loading ω is known as the asset correlation,[16] and the parameterization is chosen so that V_{it} follows the standard normal distribution. The variance of the asset return is the also measure of total risk, which is normalized to one. It can be shown that different parameterizations result in identical empirical estimates.

$$\sigma = \mathrm{var}(V_{it}) = 1 - \omega + \omega = 1 \tag{2.2}$$

This model is widely used in the literature to model discrete-time default events to estimate unconditional and conditional probabilities based on the latent factor falling below an idiosyncratic and time-varying threshold known at time t (hence, index t-1).

The model for unconditional probabilities is specified as follows:

$$PD_{it} = P(D_{it} = 1) = P(V_{it} < \lambda_{it-1}) = \Phi(\lambda_{it-1}) \tag{2.3}$$

Employing these above-mentioned unconditional models, we proceeded in two steps. As payoff is a competing outcome to performing and default, we initially estimated the probabilities of payoff (PP) in Stage 1 and control for it when estimating the probabilities of default in Stage 2. We employed logit regression for both stages. To prevent hindsight bias, we only ran the estimations with historical data. Specifically, we collected the data from year 1 to year t, run the estimation, and calibrate the predictions for year t.[17] We called this method a rolling logit.

2.3.1.1 Probabilities of payoff (Stage 1)

We estimate a PP model to explain the payoff outcomes based on the latent variable[18]

[16] The asset correlation is the correlation between the asset value return of borrower and is the same for all borrower combinations due to the specification of the Gaussian Copula.

[17] The indicators for credit performances (default, payoff, and performing) are normally determined at the end of year. Therefore, we use the data up to year t to estimate PP and PD in year t. For example, to predict the PP and PD in year 2008, we would run the estimation using data from 1999 to 2008 and calibrate the predictions for year 2008.

[18] The latent variable may be linked to borrower asset value return or credit worthiness.

V_{it} of borrower i in time t. Payoff occurs if a random trigger variable V_{it}^P falls below a deterministic threshold λ_{it-1}^P. Subscript -1 expresses that information is observed prior to this process:

$$\mathrm{P_{it}} = \begin{cases} 1, \mathrm{V_{it}^P} < \lambda_{\mathrm{it}-1}^{\mathrm{P}} \\ 0, \mathrm{V_{it}^P} \geq \lambda_{\mathrm{it}-1}^{\mathrm{P}} \end{cases} \tag{2.4}$$

We model PP as a logit model for a respective threshold:

$$\mathrm{PP_{it}} = \mathrm{P}(\mathrm{P_{it}} = 1) = \Phi(\lambda_{\mathrm{it}-1}^{\mathrm{P}}) \tag{2.5}$$

where $\Phi(\lambda_{it-1}^P)$ is the standard normal cumulative density function. The payoff threshold expressed as λ_{it-1}^P is a function of X_{it-1} which represents the set of idiosyncratic and systematic information.[19]

According to the Basel Accord, banks can build internal models based on a TTC concept, where all variables are time-invariant to limit procyclical effects on capital requirements. However, the point-in-time models are generally timelier and hence more accurate than TTC models, as they additionally include time-varying factors. We run the estimations with three models with various inclusions of time-varying variables.

The three PP model specifications are as follows:

$$\mathrm{PP_{Origination}}(\mathrm{P_{it}} = 1) = \Phi\big(\alpha_{\mathrm{P}} + \beta_{\mathrm{P}}\mathrm{OrigX_{i\tau}} + \gamma_{\mathrm{P,s}}\big) \tag{2.6}$$

$$\mathrm{PP_{+Dynamic}}(\mathrm{P_{it}} = 1) = \Phi\big(\alpha_{\mathrm{P}} + \beta_{\mathrm{P}}\mathrm{OrigX_{i\tau}} + \theta_{\mathrm{P}}\mathrm{DynX_{it-1}} + \gamma_{\mathrm{P,s}} + \theta_{\mathrm{P},\tau}\big) \tag{2.7}$$

$$\mathrm{PP_{+Macro}}(\mathrm{P_{it}} = 1) = \Phi\big(\alpha_{\mathrm{P}} + \beta_{\mathrm{P}}\mathrm{OrigX_{i\tau}} + \theta_{\mathrm{P}}\mathrm{DynX_{it-1}} + \delta_{\mathrm{P}}\mathrm{Macro_{t-1}} + \gamma_{\mathrm{P,s}} + \theta_{\mathrm{P},\tau}\big) \tag{2.8}$$

where i denotes loan, t denotes current period, and τ denotes the origination period, γ_s denotes state fixed effects, θ_τ denotes origination (vintage) effects, subscript P denotes payoff process, and subscript *-1* expresses that information is observed prior to the process. P_{it} is the

[19] We use annual observations for our regressions since default events are usually recorded at the yearly interval as industry practice. The estimated PPs enter our Stage 2 regressions for PD to control selection bias induced by the payoff decision of borrowers. The distribution of observations over categories of the independent variables may be driven by a selective process, in which payoff loans have distinctive features compared to default loans.

payoff indicator, $OrigX_{i\tau}$ are loan- and borrower-related variables at the origination time, $DynX_{it-1}$ represents dynamic idiosyncratic variables, and $Macro_{t-1}$ consists of variables capturing macroeconomic conditions. The descriptions of all variables are provided in Table 2.1.

Table 2.1:Variable definitions

Note: This table presents the variable definitions used in our paper. The data source of indicator variables, borrower characteristics, and loan characteristics is collected from Freddie Mac. The HPI at the zip code level is collected from Federal Housing Finance Agency. The income growth at the zip code level is obtained from the IRS website. Unemployment rate and HPI are sourced from the St. Louis FRED database.

Variable	Description	Models
D_{it}	The default indicator equals 1 if loans have been delinquent for 90 days or more, have been acquired by Real estate-owned acquisition or disposition, or have been involved in a short sale or charge off and zero otherwise.	Orig, +Dyn and +Macro models
P_{it}	The payoff indicator equals 1 if a loan balance becomes zero due to the prepaid, matured, or repurchase before property disposition and zero otherwise.	Orig, +Dyn and +Macro models
FICO	Borrower's credit score created by Fair Isaac Corporation	Orig, +Dyn and +Macro models
Orig LTV	The ratio between the original mortgage loan amount and house value	Orig, +Dyn and +Macro models
Orig DTI	The ratio between the borrower's monthly debt payment and total monthly income at the origination time	Orig, +Dyn and +Macro models
Refinance	The dummy variable receives a value of 1 if the mortgage is either cash-out or no cash-out refinanced and zero otherwise.	Orig, +Dyn and +Macro models
Multi_borr	The dummy variable receives a value of 1 if more than one borrower is obligated to repay the loan and zero otherwise.	Orig, +Dyn and +Macro models
Notsf	The dummy variable receives a value of 1 if the property type secured by the mortgage is not a single-family home and zero otherwise.	Orig, +Dyn and +Macro models
TPO	The dummy variable receives a value of 1 if the mortgage was originated or involved in a third-party organization such as a broker or a correspondent and zero otherwise.	Orig, +Dyn and +Macro models
Mortgage insurance	The dummy variable receives a value of 1 if a borrower is required to obtain mortgage insurance and zero otherwise.	Orig, +Dyn and +Macro models
Investment	The dummy variable receives a value of 1 if the borrower occupies a mortgage for investment purposes and zero otherwise (residence)	Orig, +Dyn and +Macro models
Orig_loansize	Natural logarithm of the original loan amount	Orig, +Dyn and +Macro models
Int_rt	Fixed contract rate	+Dyn and +Macro models
LTV_change	Difference between current LTV and Orig LTV Current LTV is the ratio of scheduled loan balance and house value. We estimate the current house value based on the HPI at the 3-digit zip code level as the product of the original house value and ratio of the current HPI and original HPI as follows:	+Dyn and +Macro models

	$$\text{House value}_t = \text{Orig House value}_\tau * \frac{\text{HPI}_{z,t}}{\text{HPI}_{z,\tau}}$$ where $\text{Orig House value}_\tau = \frac{\text{Loan balance}_\tau}{\text{LTV}_\tau}$, the subscript t represents values at the current period, and the subscript τ represents values at the origination period.	
DTI_change	Different between current DTI and orig DTI Current DTI is the ratio of annual annuity and realized borrower income. The realized borrower income is adjusted using annual income growth at the 3-digit zip code level as follows: $$\text{Realized income}_t = \text{Orig\_Income}_\tau * \frac{\text{Average gross income}_{z,t}}{\text{Average gross income}_{z,\tau}}$$ where $\text{Orig\_Income}_\tau = \frac{\text{Annuity}_\tau}{\text{DTI}_\tau}$, the subscript t represents values at the current period, and the subscript τ represents values at the origination period.	+Dyn and +Macro models
Age	The time between the current year and origination year	+Dyn and +Macro models
Age^2	Square of loan age	+Dyn and +Macro models
UER	National unemployment rate	+Macro model
HPI	National house price index	+Macro model
Contagion	The annual default rates at the 3-digit zip code level	+Macro model
PP	Probability of payoff estimated from the Stage 1 regressions	Orig, +Dyn and +Macro models

The first model, named the *Origination Model*, utilizes the TTC approach that only includes static idiosyncratic information on borrower and loan characteristics ($OrigX_{i\tau}$) recorded at the origination time. These are FICO score, LTV, and DTI at loan origination, and dummy variables indicating refinancing, multiple borrowers, not-single-family home, third-party origination channel, mortgage insurance requirement, investment purpose, and original loan size (i.e., logarithm of origination loan amount).

The second model, named the *+Dynamic Model*, incorporates dynamic idiosyncratic variables ($DynX_{it-1}$) including the changes in LTV and DTI ratios, loan age and square of loan age, contract rate, and vintage effects. The changes in LTV (DTI) are the differences between the current LTV (DTI) and the original LTV (DTI). The current LTV and DTI are adjusted by the fluctuations in local factors—house price index (HPI) growth and income growth at the three-digit zip code levels—so changes in LTV and DTI capture the effects of local systematic shocks. Loan age and its square demonstrate the effect of the borrowers' life cycles (see

Bhattacharya et al., 2019; Heinen et al., 2021). Contract rate and vintage effects are technically time-invariant, but we still consider them dynamic variables.[20] This is because the contract rate not only reflects the borrower's creditworthiness but also incorporates the influence of market conditions. Similarly, vintage effects display the fluctuation in lending standards (see Demyanyk & Van Hemert, 2011; Deng et al., 2000; Haughwout et al., 2016), reflecting market conditions.

The third model, named the *+Macro Model*, further adds macroeconomic variables ($Macro_{t-1}$) including unemployment rate, national HPI, and contagion rate. The contagion rate is calculated as the default rate at the zip code level, but it is not directly linked to borrower or loan characteristics. Therefore, we considered contagion rate as one of the macroeconomic variables.

2.3.1.2 Probabilities of default (Stage 2)

The setup of the PD model explains the latent variable[21] V_{it} of borrower i in time *t*. Default occurs if V_{it} falls below a default threshold λ_{it-1}. Subscript -1 expresses that information is observed prior to the process.

$$\mathrm{D_{it}} = \begin{cases} 1, \mathrm{V_{it}} < \lambda_{\mathrm{it-1}} \\ 0, \mathrm{V_{it}} \geq \lambda_{\mathrm{it-1}} \end{cases} \tag{2.9}$$

The Origination Model's threshold is based on the combination of the features at origination time, so the $\mathrm{PD_{Origination}}$ is often called unconditional PD. The thresholds used in the +Dynamic and +Macro models incorporate the time-varying variables, so PDs from these models are considered conditional PDs. Despite that, these specifications are usually referred to as unconditional PD models in the literature, as the systematic conditions are not explicitly specified.

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[20] All mortgages in the sample are fixed rate.

[21] The latent variable may be linked to borrower asset value return or credit worthiness in a similar fashion to the payoff process.

We derive the unconditional PD model given a standard normal distribution for V_{it} as:

$$\mathrm{PD_{it}} = \mathrm{P(D_{it} = 1) = P(V_{it} < \lambda_{it-1}) = \Phi(\lambda_{it-1})} \tag{2.10}$$

where $\Phi(\lambda_{it-1})$ is the standard normal cumulative density function. The default threshold expressed as λ_{it-1} is a function of X_{it-1}, which is the set of information on loan and borrower characteristics, including the proxies for negative equity and illiquidity as indicated in the DTM theory, the macroeconomic conditions, and payoff probability.[22]

The three PD specifications are as follows:

$$\mathrm{PD_{Origination}(D_{it} = 1) = \Phi\big(\alpha_D + \beta_D OrigX_{i\tau} + \gamma_D PP_{it} + \gamma_{D,s}\big)} \tag{2.11}$$

$$\mathrm{PD_{+Dynamic}(D_{it} = 1) = \Phi\big(\alpha_D + \beta_D OrigX_{i\tau} + \theta_D DynX_{it-1} + \gamma_D PP_{it} + \gamma_{D,s} + \theta_{D,\tau}\big)} \tag{2.12}$$

$$\mathrm{PD_{+Macro}(D_{it} = 1) = \Phi\big(\alpha_D + \beta_D OrigX_{i\tau} + \theta_D DynX_{it-1} + \delta_D Macro_{t-1} + \gamma_D PP_{it} + \gamma_{D,s} + \theta_{D,\tau}\big)} \tag{2.13}$$

where *i* denotes loan, *t* denotes current period, and τ denotes the origination period, γ_s denotes state fixed effects, θ_τ denotes origination (vintage) effects, subscript *D* denotes payoff process, and subscript *-1* expresses that information is observed prior to the process. $\mathrm{D_{it}}$ is the default indicator, $OrigX_{i\tau}$ are loan- and borrower-related variables at the origination time, $DynX_{it-1}$ represents dynamic idiosyncratic variables, and $Macro_{t-1}$ consists of variables capturing macroeconomic conditions. The definitions of these variables are the same as in the Stage 1 regressions. PP_{it} are the estimated PPs from the Stage 1 regressions. Note that the different models imply different degrees of cyclicality in which the Origination Model has the lowest and the +Macro Model has the highest cyclical variations.

2.3.2 Estimating AC

[22] Controlling for payoff probabilities is aligned with the inverse Mills ratio by Heckman (1979). We have confirmed this in unreported simulation studies.

The current Basel framework is based on a single latent systematic risk factor and assumes that idiosyncratic risks (i.e., unconditional PD) of individual loans cancel each other if the loan portfolio is sufficiently large. Banks are recommended to build internal PD models based on the TTC concept (i.e., like the Origination Model), abstracting from time-varying variables and macroeconomic factors to limit procyclical effects on capital requirements. As a result, the latent factor is the sole driver of systematic risk levels, and a single value of AC is used to calculate capital requirements for all mortgages. This practice may be unreasonable, as empirical findings have pointed out the heterogeneity in AC for different mortgages (see Lee, Rösch, & Scheule, 2021). Comparable findings on corporate loans have also proven that AC decreases with increasing PD (Cowan & Cowan, 2004; Lopez, 2004). As we propose three models estimating PDs, especially the +Dynamic and +Macro Models, which somewhat capture the effects of observed systematic risk factors, we argue that the exclusive role of the latent factor should be redefined.

We extend the Vasicek model into a two-factor model by decomposing systematic risk into observed and unobserved components. The asset return is now defined as a linear function of observed systematic risk (S_t), unobserved systematic risk (F_t) and idiosyncratic risk (U_{it}).

$$\mathrm{V_{it}} = \sqrt{\beta}\mathrm{S_t} + \sqrt{\omega}\mathrm{F_t} + \sqrt{1-\beta-\omega}\mathrm{U_{it}} \tag{2.14}$$

We assume that S_t, F_t and U_{it} are independent and identically standard normally distributed. This assumption implies that the variance of asset value, which is also the measure of total risk, is normalized to one.

$$\sigma = \mathrm{var}(\mathrm{V_{it}}) = \beta + \omega + 1 - \beta - \omega = 1 \tag{2.15}$$

where β (Beta) shows the exposure to observed systematic risk, ω (AC) shows the exposure to unobserved systematic risk, and $1-\beta-\omega$ represents idiosyncratic risk.

The estimation of AC is now associated with Beta, which both can be estimated through a conditional PD (CPD) model. We derive the CPD model as follows:

$$\begin{aligned}\mathrm{CPD_{it}} &= \mathrm{P(D_{it} = 1|S = s, F = f)}\\ &= \mathrm{P(V_{it} < \lambda_{it-1}|s_t,\ f_t)}\end{aligned}$$

$$= \Phi\left(\frac{\lambda_{it-1} - \sqrt{\beta}s_t - \sqrt{\omega}f_t}{\sqrt{1-\beta-\omega}}\right)$$

$$= \Phi\left(\frac{\lambda_{it-1}}{\sqrt{1-\beta-\omega}} - \frac{\sqrt{\beta}}{\sqrt{1-\beta-\omega}}s_t - \frac{\sqrt{\omega}}{\sqrt{1-\beta-\omega}}f_t\right)$$

$$= \Phi(a * \lambda_{it-1} + b * s_t + c * f_t) \quad (2.16)$$

where λ_{it-1} is the idiosyncratic risk factor at loan-year level, s_t is the observed systematic risk factor and f_t is the unobserved systematic risk factor.

The estimation of the CPD model with a default indicator at the loan level is a computational burden for large mortgage data sets. More importantly, AC can only be estimated for clusters (i.e., a segment of multiple loans), as default is a binary terminating event. Defaulted loans generally have no repeat default indicator. This is different in correlation studies for shares (asset pricing), where share prices are observed repeated times for given firms. Therefore, we transformed the dependent variable from a binary variable to the default rate per year. As default events are treated independently conditionally on the unobserved systematic factor, this transformation is reasonable for large portfolios (Agarwal, Chang, et al., 2012; Gordy, 2003). The transformed dependent variable is specified to follow a binomial distribution, with observation and default counts varying by time. Further, we assume that borrowers have the same idiosyncratic component to highlight the roles of systematic risk factors.[23]

The CPD model was transformed as follows:

$$\mathrm{CPD_t} = \mathrm{P}(\mathrm{D_t} = \mathrm{d_t}, \mathrm{N_t} = \mathrm{n_t}) = \Phi(a + b * s_t + c * f_t) \quad (2.17)$$

where D_t is the number of default events at year t, N_t is the number of observations in year t, s_t is the observed systematic risk factor and f_t is the realization of the unobserved systematic risk factor.

Following Hilscher and Wilson (2017), we employed mean PD by time as the proxy for

[23] In the robustness tests, we relax this assumption by allowing different idiosyncratic components across different groups of mortgages based on the types of lenders, types of recourse law, states, and risk classes. We obtain consistent results with the main analysis.

observed systematic component. By averaging PDs across several mortgages in a portfolio, we can cancel out the idiosyncratic risk component and retain the observed systematic risk. The level of observed systematic risk is expected to increase from the Origination to the +Macro Model: mean PD from the Origination Model does not capture any exposure to the observed systematic factors, mean PD from the +Dynamic Model captures local systematic shocks, and mean PD from the +Macro Model captures both local and national systematic shocks. In other words, the degree of cyclicality reflected in mean PD also increases. Mean PD, defined as the variations in average PD, is computed as follows:

$$\overline{\mathrm{PD}}_{\mathrm{t}} = \frac{\sum_{1}^{\mathrm{n_t}} \mathrm{PD_{it}}}{\mathrm{n_t}} \tag{2.18}$$

We standardized the mean PD by time, so the factor is empirically standard-normal distributed.

$$\mathrm{s_t} = \frac{(\overline{\mathrm{PD}}_{\mathrm{t}}) - 1/\mathrm{T}\sum_{1}^{\mathrm{T}}(\overline{\mathrm{PD}}_{\mathrm{t}})}{1/(\mathrm{T}-1)\left((\overline{\mathrm{PD}}_{\mathrm{t}}) - 1/\mathrm{T}\sum_{1}^{\mathrm{T}}(\overline{\mathrm{PD}}_{\mathrm{t}})^2\right)} \tag{2.19}$$

We employed a set of time (year) dummy variables as a proxy of unobserved systematic risk. These dummies reflect changes in business cycle conditions through time and impose normal distribution to estimate the exposure on unobserved systematic risk. The unobserved systematic risk factors are supposed to capture the left-unexplained systematic variations.

We employed the nonlinear mixed model for the estimation with the Gaussian quadrature approximation method and dual quasi-Newton optimization algorithm to estimate the CPD model. This method enables fitting the model by estimating probability integrated over the random effects. To reparametrize and compute the exposures to systematic factors, we let both factors enter the model linearly.

The coefficients of the CPD model are reparametrized to match the regression parameters:

$$\mathrm{a} = \frac{1}{\sqrt{1-\beta-\omega}};\ \mathrm{b} = -\frac{\sqrt{\beta}}{\sqrt{1-\beta-\omega}};\ \text{and } \mathrm{c} = -\frac{\sqrt{\omega}}{\sqrt{1-\beta-\omega}} \tag{2.20}$$

Beta (β) and AC (ω) are estimated as follows:

$$\hat{\beta} = \frac{\hat{b}^2}{1+\hat{b}^2+\hat{c}^2};\ \hat{\omega} = \frac{\hat{c}^2}{1+\hat{b}^2+\hat{c}^2} \tag{2.21}$$

Moving from using mean PD from the Origination to +Macro Models, we expect that the coefficient on the observed systematic risk factor (i.e., b) and Beta will increase, while the coefficient on the unobserved systematic risk factor (i.e., c) and AC will decrease. Given this expectation, Beta could potentially serve as a measure of cyclicality in mortgage risk. From the estimations of AC, we compute the worst-case default rate and capital ratios as follows:

$$\mathrm{WCDR} = \Phi\left(\frac{\Phi^{-1}(\mathrm{PD})+\sqrt{\mathrm{AC}}\,\Phi^{-1}(0.999)}{\sqrt{1-\mathrm{AC}}}\right) \tag{2.22}$$

$$\text{Capital ratio} = (\mathrm{WCDR} - \overline{\mathrm{PD}}) * \mathrm{LGD} \tag{2.23}$$

where PD is the annual mean PD from the Origination or +Dynamic or +Macro Models. AC is set at 15 percent under Basel framework, while it is estimated from Eq. (2.21) under the unified framework. $\overline{\mathrm{PD}}$ is the overall mean PD to capture the expected losses/loan loss provision. LGD is the downturn loss given default which is calculated at 61.34 percent from the sample.[24]

We also estimated the CPD models for subsamples that are based on several criteria, such as lender types (bank vs. nonbank), recourse types (recourse vs. nonrecourse states), and states (California vs. nine others). This practice allowed us to relax the homogenous assumption of idiosyncratic risk across different borrowers. To ensure that the impacts of observed and unobserved systematic risk factors on loans from different groups are comparable, we adjusted Eq. (2.17) by including the dummy variables for group classification and their interactions with the systematic components in the models. This method allowed us to estimate the exposures to observed and unobserved systematic factors of two or more groups concurrently. The CPD model for subsample analyses is now designed as follows:

$$\mathrm{CPD}_t = P(N_{kt} = n_k | S_t = s_t,\ F_t = f_t)$$

$$= \Phi\left(a_0 + \sum_{k=1}^{k}(a_k * \Delta_k) + b * s_t + \sum_{k=1}^{k}(c_k * s_t * \Delta_k) + d * f_t + \sum_{k=1}^{k}(e_k * f_t * \Delta_k)\right)$$

[24] The calculation for LGD is present in Appendix 2.F.

(2.24)

where N_{kt} is the number of default events for group k at year t, Δ_k represents the dummy variables, and k is the number of dummy/interaction variables less one (for the reference category).

Class-specific Beta (β) and AC (ω) is computed from the estimated parameters as follows:

$$\hat{\beta}_0 = \frac{\hat{b}^2}{1+\hat{b}^2+\hat{d}^2};\ \hat{\omega}_0 = \frac{\hat{d}^2}{1+\hat{b}^2+\hat{d}^2} \tag{2.25}$$

$$\hat{\beta}_k = \frac{(\hat{b}+\hat{c}_k)^2}{1+(\hat{b}+\hat{c}_k)^2+(\hat{d}+\hat{e}_k)^2};\ \hat{\omega}_k = \frac{(\hat{d}+e_k)^2}{1+(\hat{b}+\hat{c}_k)^2+(\hat{d}+\hat{e}_k)^2} \tag{2.26}$$

where reference groups are banks, nonrecourse states, and California.

2.3.3 Pricing tests

The estimations of PDs and AC are two main components in calculating unexpected loss or capital requirements. These should be reflected in the mortgage interest rate. Following Liu et al. (2012), we analyzed whether mortgage interest rates at origination reflect the impact of systematic risk. We measure the exposure to systematic risk as the unexpected loss, as this is the basis for lender capital and hence funding costs. According to Basel Accord, the unexpected loss is calculated as the difference between the 99th percentile of the CPD (i.e., VaR) and the expected loss. This is also considered the capital requirement for lenders to remain solvent over the one-period horizon.

$$\mathrm{UL_{srisk}} = \Phi\left(\frac{\Phi^{-1}(\mathrm{PD})+\sqrt{\mathrm{AC}}\Phi^{-1}(0.999)}{\sqrt{1-\mathrm{AC}}}\right) - \mathrm{PD} \tag{2.27}$$

where PD is estimated for each loan at the origination time from the two-stage logit regressions specified in Eq. (2.11)–(2.13); $\Phi^{-1}(PD)$ is the inversed function of unconditional PD; AC is the exposure to unobserved systematic risk factors; and *99.9 percent* is the conservative value of the single systematic risk factor according to Basel III to represent the state of the global economy.

To create more heterogeneity in systematic risk levels, we randomly split mortgages into subsamples with approximately 10,000 loans each and estimated systematic risk levels for each subsample. As a result, we obtained around 2,000 subsamples and had 2,000 variations of unexpected loss for the pricing regression.

Loan-level prices may be based on loan and borrower characteristics according to underwriting criteria. Therefore, we add FICO, original DTI, original LTV, original loan size, and various dummy variables for refinance, multiple borrowers, non-single-family property, third-party origination, mortgage insurance, and investment purposes. To capture the nonlinear effects from the main idiosyncratic risk factors such as FICO, DTI, and LTV, we include their splines in the model.[25] We included the national average rate on a 30-year mortgage[26] in the pricing equation. This allowed us to capture the variations in mortgage rates compared to the national rate, as well as vintage effects. We also included state and vintage dummy variables to control state regulation and lending competition. Standard errors are clustered by lender to control for lender's standard and risk appetite. We defined the pricing regression as follows:

$$\mathrm{Int\_rt}_{i,\tau} = \alpha + \beta \mathrm{UL}_{srisk,i} + \gamma \mathrm{Rate}_{\tau} + \delta X_{i,\tau} + \eta_s + \mu_{\tau} + \varepsilon_l \tag{2.28}$$

where UL is the unexpected loss reflecting the borrower's exposure to systematic risk factor, Rate is the national average of 30-year mortgage; X represents the loan and borrower characteristics and their splines, η_s represents the states fixed effects, μ_τ represents vintage fixed effects, ε_l represents lender clusters. All observations were recorded at the origination time.

2.4 Data description

We obtain data on mortgage loans from the FHFA, which includes information on mortgage contract characteristics at the origination period as well as monthly loan performance. The mortgages originate from banks and nonbank lenders and are securitized by the US Federal

[25] The FICO and DTI splines are constructed by percentiles. The LTV splines are constructed at the absolute knots which are 70%, 75%, 80%, and 85% as most loans fall into the in-between ranges.

[26] We collect the data on national average rate on 30-year mortgages from FRED St. Louis FED database https://fred.stlouisfed.org/series/MORTGAGE30US.

Home Loan Mortgage Corporation.[27] These data are used to construct static and dynamic loan- and borrower-related characteristics.

The original dataset consists of more than 2 billion observations at monthly intervals from February 1999 to December 2019. Since mortgages with different maturities may have different term premiums, we restrict our analysis to only 30-year fixed-rate mortgages. We also dropped observations where the information on borrower and loan characteristics such as FICO, DTI, LTV, occupancy status, mortgage insurance, number of borrowers, property type, loan purpose, and origination channel is not available. Loans ceasing their existence in the sample due to third-party sale or reperforming sale were excluded. After recording the default events of loans that were delinquent for 90 days or more, or entered foreclosure, we removed the loans in the following periods from the data set. The sample was reduced to around one billion observations after all filter rules. From this data set, we constructed all variables related to loan and borrower characteristics (OrigX) at the origination time.

For the dynamic idiosyncratic variables (DynX), we further collected the monthly data on HPI from the FHFA and gross income from the IRS at the three-digit zip code levels over the period 1999 to 2019.[28] To capture the continuous changes, we calculate the cumulative growth in HPI and average gross income and then adjust the borrowers' house value and realized income. We then merge these data with the mortgage data and calculate the current LTV and DTI ratios and their changes compared to the original LTV and DTI ratios.[29] The other variables in this group were loan age and interest rate. Loan age is the difference between the current year and the origination year. The interest rate is the contract rate determined at the origination time and provided in the mortgage data.

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[27] The FDIC (2019) stated nonbanks sold nearly all of their originations (97%) while banks only sold half of their 1-4 family originations.

[28] FHFA: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

IRS: https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi

[29] We provide the equations to calculate the changes in LTV and DTI in Table 2.1.

Apart from loan and borrower characteristics, we also utilize mortgage data to construct the proxy for the contagion effect, which is the default rates at zip code levels over time. This variable is categorized as being part of a group of macroeconomic factors (Macro). We also collected the national HPI and unemployment rate at annual intervals from the Federal Reserve Bank of St. Louis database over the research period.

We annualize the monthly data (i.e., OrigX, DynX, and contagion) as many industry metrics are based on a one-year reporting period. We take the maximum values for dummy variables representing loan purpose, multiple borrowers, property types, origination channel, mortgage insurance, and occupation type. For other variables generated at origination times, such as FICO score, original DTI, original LTV, loan size, and interest rate, we take the first observations as these values do not change over time. To annualize current LTV, we take the last observations on scheduled loan amount and adjusted house values, as these values are time dependent. To annualize the current DTI, we take the sum of the monthly annuity and realized income. For contagion, we take the average contagion rate per zip code-year.

Table 2.2 presents the descriptive statistics on all variables for the full sample and subsamples of default and payoff loans.

The average FICO score is 737, which is considered a high credit rating. The original LTV is 72.8 percent (the median is roughly 80 percent), reflecting a standard requirement from banks that borrowers are usually required to have at least 20 percent of the house value as a deposit. The average original DTI is 34 percent, which means that 34 percent of borrowers' income is spent on paying mortgage debt, making it one of the biggest spending categories for households. The change in LTV is approximately -7.7 percent, which is due to amortization and house price gains. Due to increases in income, DTI is approximately -2.6 percent lower than the original DTI.

Table 2.2: Descriptive Statistics

Note: This table shows the descriptive statistics of all variables for the full sample, default, and payoff loans. We present the mean, standard deviation, and min and max for the full sample. We only show mean and standard deviation to reserve space for the default and payoff subsamples. The definitions of all the below variables are presented in Table 2.1.

	Full sample				**Default**		**Payoff**	
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Mean	Std. Dev
D_{it}	0.008	0.091	0	1	1	0	0	0
P_{it}	0.135	0.341	0	1	0	0	1	0
FICO	737	52.89	300	850	689	55.731	735	52.631
Orig LTV	0.728	0.162	0.06	1.05	0.788	0.13	0.723	0.162
Orig DTI	0.34	0.113	0.01	0.65	0.388	0.113	0.339	0.115
Refinance	0.558	0.497	0	1	0.608	0.488	0.561	0.496
Multi_borr	0.556	0.497	0	1	0.417	0.493	0.594	0.491
NotSF	0.26	0.438	0	1	0.221	0.415	0.255	0.436
TPO	0.516	0.5	0	1	0.602	0.489	0.528	0.499
Mgt insurance	0.204	0.403	0	1	0.328	0.469	0.189	0.391
Investment	0.06	0.238	0	1	0.061	0.239	0.05	0.217
Orig_loansize	11.987	0.573	8.517	14.201	11.912	0.578	12.019	0.552
Int_rt	0.055	0.011	0.025	0.12	0.062	0.009	0.058	0.011
LTV_change	-0.077	0.178	-1	16.886	0.099	0.467	-0.086	0.188
DTI_change	-0.026	0.041	-2.873	9.348	-0.026	0.053	-0.029	0.043
Loan age	3.173	3.128	0	20	4.284	2.849	3.974	2.962
UER	0.06	0.019	0.037	0.096	0.074	0.02	0.065	0.019
HPI	525	63.627	352.08	638.37	509	49.179	507	59.723
Contagion	0.008	0.009	0	0.5	0.019	0.021	0.009	0.008
No of obs.	102,321,170				776,042		13,716,242	

We observed 776,042 default events, representing an average default rate of roughly 0.8 percent. We detect that default loans have lower FICOs, higher LTVs, and higher DTIs. These loans are likely to relate to refinance loans, single borrowers, originating through third-party channels, including mortgage insurances and higher contract rates. Default loans also experience a positive change in LTV, longer loan age, higher unemployment rate, lower national HPI, and higher contagion rate.

We observe 13,716,242 payoff events equivalents to a payoff rate of 13.5 percent. We notice that payoff loans experience a larger drop in LTVs, which is induced by an increase in house values. In fact, borrowers tend to take advantage of house price appreciations to pay off the mortgage (LaCour-Little et al., 2010). The differences in the other variables are negligible.

2.5 Empirical results

In this section, we first present the model outputs for PP and PD. Since we utilize the rolling logit method, we obtain up to 19 models.[30] We provide the estimations from models utilizing the full sample and the 1999–2009 period when the default rate peaks. Subsequently, we report the outputs of CPD models and the estimations of systematic risk levels. Finally, we present the results of the pricing tests.

2.5.1 Probabilities of payoff

Table 2.3 presents the estimation results of the multivariate PP models based on the logit regressions using the full sample and the 1999–2009 period.[31] The signs of coefficients are consistent regardless of sample size, but the magnitudes of those from the full sample are smaller than those from the 1999–2009 subsamples.

The purpose of controlling the payoff probability is to reduce selection bias (Heckman, 1979). We found a positive correlation between FICO and payoff likelihood and inverse correlations of original LTV and DTI with payoff likelihood. Refinance loans, including mortgage insurances, and support for investment properties are less likely to payoff. In contrast, loans with multiple borrowers, larger loan sizes, and higher contract rates have higher likelihoods of payoff. An increase in LTV reduces the payoff probability, while an increase in DTI motivates borrowers to prepay mortgages. These results indicate that borrowers who experience a reduction in house value may avoid prepayments, as it incurs an immediate loss in their built-up equity. Still, borrowers experiencing a decrease in income may find a way to pay off loans as quickly as possible to relieve their financial burden. Regarding model fit, the AUROC and R-square values constantly increase from the first to the last models, meaning that

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[30] The first model utilizes the data from 1999 to 2000, the second model utilizes the data from 1999 to 2001, and so on.

[31] We obtain the consistent results when employing either probit or multinomial logit regressions.

a more complex model explains a greater degree of variation in the payoff risk.

2.5.2 Probabilities of default

Table 2.4 shows the estimation results for multivariate PD models based on the logit regressions using the full sample and the 1999–2009 period.

All estimates are highly consistent across the three models and are in line with the literature. Lower FICO scores, higher LTV, and higher DTI ratios at origination have higher PDs. These results are consistent with numerous studies in the literature (Chan et al., 2016; Elul et al., 2010; Mayer et al., 2009). Loans that are refinanced, originating through third-party channels, including mortgage insurance, with larger loan sizes or higher contract rates, are riskier and imply a greater PD. In contrast, dummies for multiple borrowers, non-single-family property, and investment occupancy have a negative coefficient.

The coefficients on changes in LTV and DTI are positive in all models, indicating that increases in LTV and DTI intensify the risk level and trigger default events. These results confirm the prevalence of DTM theory in explaining default risk. Our results also confirm the nonlinear effects of loan age on default, as loan age's coefficient is positive and that of loan age squared is negative.

In terms of macroeconomic variables, the unemployment rate and contagion show positive impacts on the default probability. A positive coefficient of unemployment shows that borrowers may not continue serving loans if the unemployment rate surges. This result is consistent with Elul et al. (2010) and supports the DTM theory. The effect of contagion on PD is expected. Borrowers may experience negative equity and stop serving loans on distressed property (Goodstein et al., 2017).

Table 2.3:Estimation of payoff probability (Stage 1)

Note: This table presents the parameter estimates for payoff probabilities (PP). We present the estimation results with the 1999–2009 and the full samples. The Origination Model for PP is specified in Eq. (2.6). The +Dynamic Model for PP is specified in Eq. (2.7). The +Macro Model for PP is specified in Eq. (2.8). The dependent variable in all models is the payoff indicator. The definitions of explanatory variables are provided in Table 2.1. The coefficients on dummies for origination years (i.e., vintage effects) are skipped for simplicity. Standard errors are clustered at the state level and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the AUROC and max rescaled R-square. The number of observations is also provided.

	1999 – 2009 period			**Full sample**		
	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
Intercept	-1.64*** (0.323)	-17.611*** (0.541)	-26.925*** (0.759)	-2.257*** (0.196)	-14.482*** (0.415)	-12.36*** (0.309)
FICO	-0.001*** (0)	0.001*** (0)	0.001*** (0)	-0.001*** (0)	0.002*** (0)	0.002*** (0)
Orig LTV	-0.076 (0.1)	-0.502*** (0.096)	-0.523*** (0.113)	-0.216*** (0.05)	-0.448*** (0.065)	-0.412*** (0.098)
Orig DTI	-0.054* (0.028)	0.215*** (0.032)	0.219*** (0.029)	-0.026 (0.031)	-0.019 (0.036)	-0.002 (0.038)
Refinance	-0.184*** (0.019)	-0.087*** (0.02)	-0.074*** (0.018)	-0.051*** (0.008)	-0.084*** (0.017)	-0.081*** (0.015)
Multi_borr	0.132*** (0.006)	0.087*** (0.011)	0.088*** (0.01)	0.149*** (0.006)	0.091*** (0.011)	0.094*** (0.008)
Notsf	-0.049** (0.024)	0.007 (0.027)	0.003 (0.025)	-0.032* (0.019)	0.036 (0.023)	0.034* (0.021)
TPO	0.042 (0.032)	0.015 (0.019)	0.006 (0.018)	0.054*** (0.018)	0.001 (0.015)	-0.01 (0.015)
Mgt insurance	0.07*** (0.02)	-0.084*** (0.02)	-0.082*** (0.021)	-0.085*** (0.014)	-0.03*** (0.01)	-0.047*** (0.012)
Investment	-0.214*** (0.015)	-0.561*** (0.038)	-0.583*** (0.042)	-0.214*** (0.011)	-0.37*** (0.024)	-0.394*** (0.025)
Orig loansize	0.058** (0.027)	0.642*** (0.036)	0.608*** (0.033)	0.09*** (0.015)	0.585*** (0.031)	0.548*** (0.025)
Interest_rate		0.795*** (0.032)	0.817*** (0.034)		0.566*** (0.03)	0.569*** (0.029)
LTV_change		-0.935***	-1.432***		-0.334***	-0.475***

		(0.259)	(0.215)		(0.085)	(0.106)
DTI_change		1.42***	1.351***		1.631***	1.769***
		(0.444)	(0.33)		(0.438)	(0.42)
Age		1.146***	0.694***		0.438***	0.487***
		(0.019)	(0.025)		(0.01)	(0.008)
Age^2		-0.154***	-0.151***		-0.03***	-0.032***
		(0.004)	(0.005)		(0.001)	(0.001)
UER			0.727***			0.103***
			(0.031)			(0.014)
HPI			0.012***			-0.004***
			(0.001)			(0)
Contagion			-21.589***			-29.146***
			(3.812)			(3.18)
Vintage FEs	No	Yes	Yes	No	Yes	Yes
State cluster	Yes	Yes	Yes	Yes	Yes	Yes
AUROC	0.54	0.756	0.784	0.537	0.700	0.715
Max-rescaled R-square	0.004	0.181	0.222	0.004	0.105	0.121
No of obs.	42,764,278	41,785,815	41,785,815	102,321,170	100,503,213	100,503,213

Table 2.4: Estimation of default probability (Stage 2)

Note: This table presents the parameter estimates for probabilities of default (PD). We present the estimation results with the 1999 – 2009 sample and the full sample. The Origination Model for PD is specified in Eq. (2.11). The +Dynamic Model for PD is specified in Eq. (2.12). The +Macro Model for PD is specified in Eq. (2.13). The dependent variable in all models is the default indicator which is either being at least 90-day delinquent or being foreclosed. The definitions of explanatory variables are provided in Table 2.1. The coefficients on dummies for origination years (i.e., vintage effects) are skipped for simplicity. Standard errors are clustered at the state level and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the AUROC, rescaled R-square. The number of observations is also provided.

	1999 – 2009 sample			Full sample		
	Origination	+Dynamic	+Macro	Origination	+Dynamic	+Macro
Intercept	4.774***	-6.081***	-12.636***	1.474**	-5.925***	-8.896***
	(0.875)	(1.408)	(0.969)	(0.611)	(1.078)	(0.683)
FICO	-0.013***	-0.011***	-0.011***	-0.012***	-0.009***	-0.01***
	(0)	(0)	(0)	(0)	(0)	(0)
Orig LTV	2.786***	3.005***	2.775***	2.513***	2.386***	2.427***
	(0.134)	(0.124)	(0.114)	(0.14)	(0.156)	(0.131)
Orig DTI	1.837***	1.568***	1.582***	2.846***	1.798***	1.812***
	(0.094)	(0.11)	(0.105)	(0.115)	(0.099)	(0.094)
Refinance	0.315***	0.364***	0.343***	0.383***	0.367***	0.383***
	(0.048)	(0.031)	(0.027)	(0.037)	(0.026)	(0.019)
Multi_borr	-0.54***	-0.634***	-0.606***	-0.518***	-0.541***	-0.543***
	(0.044)	(0.015)	(0.014)	(0.02)	(0.014)	(0.012)
Notsf	-0.237***	-0.18***	-0.163***	-0.075	-0.066	-0.077***
	(0.042)	(0.038)	(0.025)	(0.064)	(0.045)	(0.026)
TPO	0.421***	0.329***	0.32***	0.245***	0.14***	0.143***
	(0.035)	(0.029)	(0.027)	(0.027)	(0.019)	(0.018)
Mgt insurance	0.155***	0.194***	0.185***	0.054*	0.11***	0.124***
	(0.045)	(0.026)	(0.023)	(0.031)	(0.028)	(0.023)
Investment	0.147*	0.004	-0.09	0.199**	-0.01	0.035
	(0.087)	(0.083)	(0.075)	(0.079)	(0.053)	(0.05)
Orig loansize	-0.218**	-0.05	0.12*	-0.026	0.096	0.073
	(0.106)	(0.082)	(0.071)	(0.07)	(0.071)	(0.059)
Interest_rate		0.778***	0.924***		0.533***	0.482***
		(0.077)	(0.052)		(0.038)	(0.028)
LTV_change		2.74***	1.979***		0.868**	0.579*

		(0.344)	(0.275)		(0.412)	(0.319)
DTI_change		0.677***	0.767***		1.044**	0.428
		(0.224)	(0.248)		(0.441)	(0.329)
Age		1.189***	1.071***		0.412***	0.276***
		(0.055)	(0.048)		(0.029)	(0.013)
Age^2		-0.124***	-0.123***		-0.029***	-0.017***
		(0.004)	(0.004)		(0.003)	(0.001)
UER			0.329***			0.182***
			(0.023)			(0.021)
HPI			0.004***			0.005***
			(0.001)			(0.001)
Contagion			16.158***			23.302***
			(0.85)			(3.911)
PP	-8.528***	-1.262	-3.324***	-2.517***	0.446*	1.113***
	(2.79)	(0.778)	(0.59)	(0.697)	(0.271)	(0.202)
Vintage FEs	No	Yes	Yes	No	Yes	Yes
State cluster	Yes	Yes	Yes	Yes	Yes	Yes
AUROC	0.807	0.861	0.867	0.774	0.846	0.856
Max-rescaled R-square	0.110	0.173	0.183	0.089	0.156	0.177
Number of observations	35,840,163	34,956,950	34,956,950	102,321,170	100,064,218	100,064,218

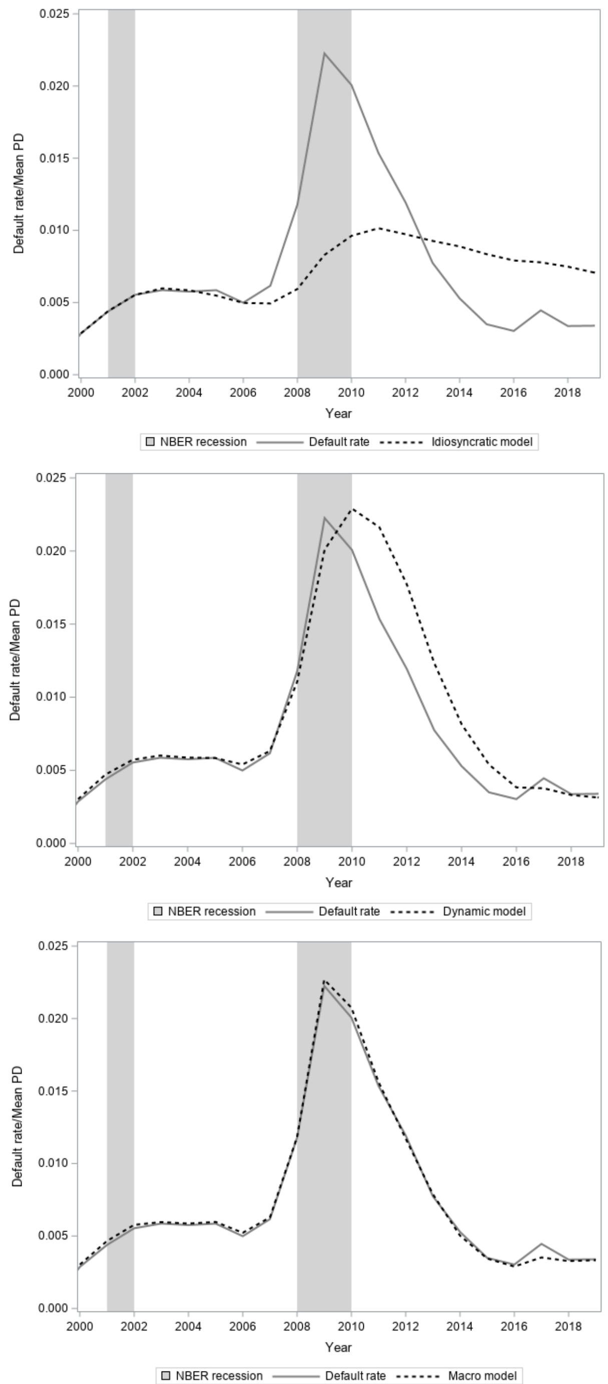

Figure 2.1: Default rate and Mean PD

Note: This figure shows the fluctuations of default rate (solid line) and Mean PD (dash line) over time for three different PD models, including the Origination Model specified in Eq. (2.11), the +Dynamic Model specified in Eq. (2.12), the +Macro Model specified in Eq. (2.13). The shaded areas indicate the recession periods as defined by NBER. We compute the difference between the default rate and estimated PDs for each year and take the averages as the mean deviation. The mean deviation between the observed default rate and estimated PDs is -0.09 percent for the Origination Model, 0.12 percent for the +Dynamic Model, and 0.01 percent for the +Macro Model.

The model fit measured by the AUROC ratio increases from the Origination to the +Macro Model. The pseudo-R-square also improves across the three models. The more complex model explains the variations in default risk to a greater degree. The +Macro Model is also superior to the Origination Model in capturing observed systematic risk factors.

The average PD from the Origination Model is quite flat and peaks in 2008, which is due to the tightened lending standards on mortgages during the GFC. It is obvious that the estimates from the Origination Model do not align with the default rate. Rajan et al. (2015) acknowledges a poor model performance in predicting loan creditworthiness. The mean PD of the +Dynamic Model is more aligned with the default rate as the local (i.e., three-digit zip code levels) house price and income growth are controlled through the inclusion of LTV and DTI changes. Despite including dynamic idiosyncratic information, the fluctuations in default rate are not properly captured by this model, especially during the crisis and post-crisis periods. The gap closes for the +Macro Model, in which the dashed line showing the average of PD closely follows the solid line of default rate.

When lenders use a more accurate model to predict default risk, it implies that they have access to more information at the time of loan issuance. This allows for a better assessment of the creditworthiness of borrowers and makes for more informed lending decisions. Ultimately, this increased accuracy in lending decisions can contribute to a more efficient and stable mortgage market, benefiting both lenders and borrowers.

2.5.3 Measures of systematic risk level

2.5.3.1 Full sample analysis—homogeneity across mortgages

Table 2.5 presents the regression of the CPD models specified in Eq. (2.17) in Panel A, and the estimates for systematic risk levels in Panel B according to Eq. (2.21). CPD models are different from the observed systematic risk factor proxy, which is the mean PD from the corresponding PD models. In the last panel, we present the statistics related to model accuracy, including log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The rule of thumb when examining these statistics is that the smaller the more accurate the models are.

The results indicate that the magnitude of the coefficient on the observed systematic risk factor increases and that of the unobserved counterpart decreases when we incorporate more systematic shocks into the CPD models. From the economic interpretation, the coefficient on the observed factor increases from 0.097 to 0.234, indicating that an increase of one standard deviation unit leads to an increase of 9.7 percent to 23.4 percent in the default rate. Meanwhile, the coefficient of the unobserved factor reduces from 0.191 to 0.053. As we control for more macroeconomic factors in the +Dynamic and +Macro Models, the observed effect becomes more prominent in explaining the variation of default rates. The frailty effect reduces in magnitude but remains meaningful. This hints at the complementary effect of observed and unobserved factors in explaining the default risk, implying the exposure to frailty factor could be smaller if the exposure to observed factor is increasing.

Table 2.5: Estimates of the CPD model (Stage 3)

Note: Panel A of this table presents the estimation results of the CPD model specified in Eq. (2.17). The dependent variable is the number of default events. The independent variable includes observed and unobserved systematic risk factors. Panel B of this table presents the estimates of Beta and AC, as specified in Eq. (2.21). The total systematic risk level is the sum of beta and AC. Panel C of this table shows the statistics related to model performances, including AIC, BIC, and -2 Log-likelihood. The names of the CPD models are consistent with the PD models as we employ the mean PD from these models. Specifically, the Origination Model for PD is specified in Eq. (2.11); the +Dynamic Model for PD is specified in Eq. (2.12); and the +Macro Model for PD is specified in Eq. (2.13). Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively.

	Origination	**+Dynamic**	**+Macro**
Panel A: CPD Equation			
a	-2.466***	-2.465***	-2.464***
	(0.044)	(0.016)	(0.012)
b	0.097**	0.223***	0.234***
	(0.038)	(0.017)	(0.013)
c	0.191***	0.071***	0.053***
	(0.03)	(0.011)	(0.008)
Panel B: Systematic risk levels			
Beta	0.009	0.047***	0.052***
	(0.007)	(0.007)	(0.005)
AC	0.035***	0.005***	0.003***
	(0.011)	(0.001)	(0.001)
Total systematic risk	0.044***	0.052***	0.054***
	(0.012)	(0.007)	(0.005)
Panel C: Model performance			
AIC	449.6	410.1	398.6
BIC	452.6	413.1	401.6

-2 Log-likelihood	443.6	404.1	392.6

We reparametrize systematic risk levels based on sensitivities to systematic risk factors. As we move from the Origination to +Macro Models, we find that the exposure to the observed factor (i.e., Beta) significantly increases from 0.9 percent to 5.2 percent, and the exposure to the unobserved factor (i.e., AC) decreases from 3.5 percent to 0.3 percent. All three models intend to explain the same variations in default rates, so the fluctuations in Beta and AC lead to changes in their contributions to total systematic risk. Beta's contribution increases from 20 percent to 95 percent, while AC's contribution decreases from 80 percent to 5 percent when changing from the Origination to the +Macro Model.[32] We visualize the changes in Beta and AC across the three models in Figure 2.2.

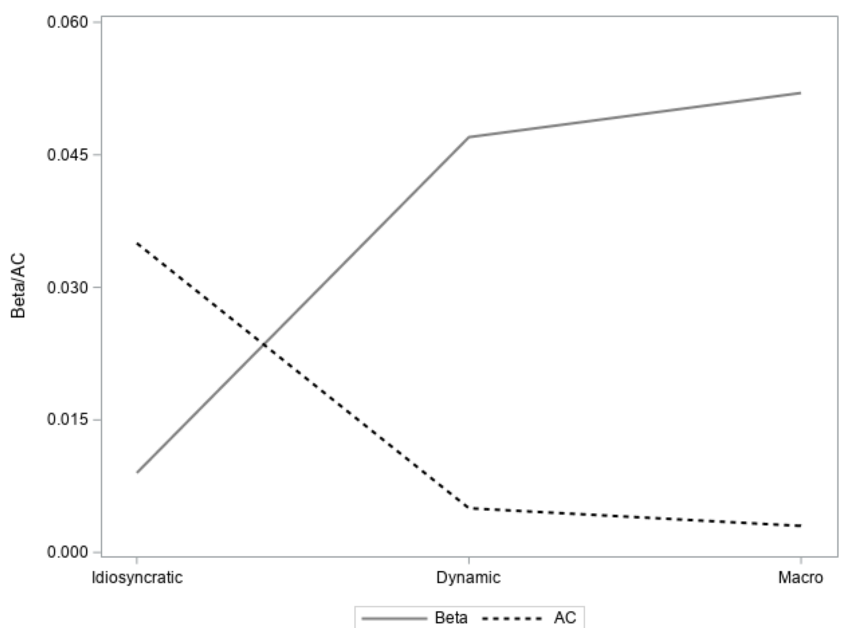

Figure 2.2: Beta and AC estimates

Note: This figure plots the estimates of Beta (solid line) and AC (dash line) as specified in Eq. (2.21) based on the estimation results of three different CPD models. Each CPD model uses the standardized mean PD from the

[32] The Beta and AC estimations are comparable if the monotone inverse standard normal transformation for mean PD is used.

corresponding PD models, including the Origination Model specified in Eq. (2.11), the +Dynamic Model specified in Eq. (2.12), the +Macro Model specified in Eq. (2.13).

Note that the stand-alone and combined magnitudes of the estimations are lower than the Basel benchmark, which is 15 percent. This finding could be because our default indicator only captures being delinquent for at least 90 days or being foreclosed due to data limitations. Regulators could require the inclusion of other events, such as loan write-offs and personal bankruptcies, which are less frequent. Despite that, our lower estimated systematic risk level strongly indicates that GSE's risk is typically lower than the bank's risk as GSE could eliminate their liquidity and credit risk efficiently through pooled issuance of MBS. Therefore, we suggest applying a lower systematic risk level for GSE-held mortgages.

Regarding model accuracy, the literature often uses AUROC to demonstrate model performance. Since we do not examine the nested models where the later version extends the previous one, using AUROC is not meaningful. This is because all three models remain two-factor models, and the explanatory power comes from observed or unobserved factors. The difference across the three models lies in the decomposition of systematic risk; hence, we would rely on absolute measures such as log-likelihood, AIC, and BIC to examine model accuracy. The last panel of Table 2.5 shows that all three statistics become smaller as we move from the Origination to the +Macro Model. The results indicate that the model properly controlling for the observed systematic risk proves to be the best for capturing default variances.

However, the large incorporation of observed systematic risk factors likely amplifies the procyclicality in capital requirements. We look at three metrics—mean PD, WCDR, and capital ratio—and compute their minimum, maximum, and Max-Min differences. These estimations demonstrate the peak-to-trough variations in capital components and levels, in which the smaller max-min difference implies a lower level of cyclicality. We report the results in Table 2.6. Panel A is for mean PD, Panel B is for WCDR and maximum capital ratio under the Basel framework, and Panel C presents similar metrics to Panel B, but the results are associated with the unified framework. Upon initial observation, it is evident that the three models exhibit similar overall mean PD and share the same minimum values for annual mean PD. Therefore, our attention is directed toward analyzing the maximum capital ratio, which corresponds to the maximum value of annual mean PD. We discuss the extent to which the more risk-sensitive PD models contribute to the procyclicality in capital requirements.

In Panel A, we observe that the max-min difference in mean PD is the smallest for the Origination Model and gets higher for the +Dynamic and +Macro Models. These findings imply an increase in the cyclicality of capital components when incorporating more macroeconomic factors into the PD models. Note that the fit between the estimated PDs from the +Macro Model and the observed default rate is the most appropriate, indicating the most suitable model for banks' risk management. There is a trade-off between capturing risk level and dampening procyclicality among the three models. Using the TTC approach to build a PD model would help to reduce the variations in inputs of the capital equation. Still, the market conditions are poorly captured and limit lenders in managing risk efficiently. In contrast, using a point-in-time approach in forming PD models with proper inclusion of systematic shocks provides a great risk evaluation but increases the procyclicality in capital requirements.

By linking Table 2.5 and Table 2.6 results, we notice that both Beta and max-min variation in mean PD increase from the Origination to the +Macro Model. This implies that Beta could serve as a measure of procyclicality and potentially be used to construct the counter-cyclical measure for capital requirements.[33]

When examining the calculations on the WCDR and capital requirements under the Basel framework in Panel B, a similar trend emerges, as seen in the mean PD analysis. The overall means and minimum values exhibit similarities across the three models. However, the key differences lie in the maximum values of WCDR, with the Origination Model recording the smallest value and the +Dynamic and +Macro Models producing higher estimates. This leads to an increasing trend in the Max-Min difference in WCDR and the capital ratio as the PD models start controlling for macroeconomic conditions and becoming more risk-sensitive. For this reason, regulators tend to encourage the use of the TTC-based PD model for estimating capital charges to dampen the procyclicality in capital requirements.

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[33] Some countercyclical solutions have been discussed in the literature. We do not go further in this path in this study, but we could address it in the future study.

The current Basel framework allows banks to estimate the average PD only and utilize a single value of AC as the exposure to an unobserved systematic risk factor (i.e., 15 percent) in calculating capital requirements. This practice lays support for using the TTC approach in estimating PDs, aiming to dampen procyclicality in capital requirements. However, we argue that AC for mortgages should be downward adjusted if more macroeconomic conditions are controlled because total systematic variations are explained through the combination of observed and unobserved systematic factors. This practice has been applied for corporate, sovereign, and bank exposures, where the asset correlation parameter decreases with the increasing PDs.[34] Using the two-factor CPD models, we have clarified that AC decreases with increasing Beta. Suppose these estimated ACs are utilized in the capital equation. In that case, it will generate the flattening effect, meaning that the capital charge due to observed systematic risk is increasing and that related to unobserved systematic risk is decreasing.

Table 2.6: Analysis of procyclicality and capital charges

Note: This table presents the analysis of procyclicality in capital requirements across the three models. In Panel A, we reported the overall mean, minimum, and maximum values of annual mean PD along with their Max-Min difference. In Panel B, we reported the mean, minimum, maximum and the Max-Min difference of worst-case default rate and maximum capital ratios, using the regulatory value of AC (15 percent) from the Basel framework. In Panel C, we present the similar findings as in Panel B, but this time we utilize the estimated ACs from the unified framework, which are reported in Panel B of Table 2.5.

	Origination	**+Dynamic**	**+Macro**
Panel A: Cyclicality of annual mean PDs			
Mean PD	0.007	0.009	0.008
Min PD	0.003	0.003	0.003
Max PD	0.010	0.023	0.023
Max-Min difference	0.007	0.020	0.020
Panel B: Cyclicality of WCDR and capital ratio, Basel framework			
Mean WCDR	0.086	0.101	0.092
Min WCDR	0.045	0.047	0.045
Max WCDR	0.111	0.193	0.191
Max-Min difference	0.067	0.146	0.146
Max capital ratio	0.067	0.118	0.118
Panel C: Cyclicality of WCDR and capital ratio, Unified framework			
Mean WCDR	0.028	0.015	0.012
Min WCDR	0.013	0.006	0.005

[34] The relationship between AC and PD for these exposures are expressed as: $AC = 0.12(1 + e^{-50*PD})$.

Max WCDR	0.038	0.037	0.033
Max-Min difference	0.025	0.031	0.028
Max capital ratio	0.020	0.018	0.016

Panel C of Table 2.6 shows the WCDR and capital ratio, calculated under the unified framework. WCDR exhibits a decreasing pattern from the Origination to +Macro Models across the overall mean, minimum, and maximum values. This consistent pattern is attributed to the decrease in AC. Given the decreasing trend in the WCDR, it logically follows that the capital charges under the unified framework should also decrease accordingly. The unified framework could be a suitable and effective approach for calculating the capital requirement, as it adequately captures the changing risk dynamics and adjusts the capital charges accordingly.

The most significant savings are observed for low-risk mortgages, with the minimum WCDR decreasing from 1.3 percent to 0.5 percent. The maximum WCDR also experiences a reduction from 3.8 percent to 3.3 percent. Consequently, the Max-Min differences in WCDR are as follows: The Origination Model demonstrates the lowest variation at 2.5 percent, followed by the +Macro Model with 2.8 percent, and the +Dynamic Model with 3.1 percent. The observed increase in the Max-Min difference in WCDR signifies a corresponding rise in the cyclicality of capital charges when incorporating more macroeconomic conditions, as anticipated. However, the increase is much smaller than the Basel framework, in which this Max-Min difference increases from 6.7 percent to 14.6 percent. Looking at the Origination Model—showing the most alignment between the Basel and unified framework, we can see the reduction in peak-to-trough variation from 6.7 percent under Basel to 2.5 percent under the unified framework. Hence, adopting the proposed two-factor risk model could mitigate the procyclicality in capital charges.

We finally uncover that the maximum capital ratio decreases from 2 percent in the Origination Model to 1.7 percent in the +Dynamic Model and 1.5 percent in the +Macro Model. This reduction can be attributed to lower AC and a decrease in expected loss. The higher PD levels from more risk-sensitive models lead to higher expected loss, further decreasing the capital requirement. If we incorporate the macroeconomic conditions without adjusting the AC under Basel, the maximum capital ratio increases from 6.7 percent to 11.3 percent. This is because the exposure to observed systematic risk is doubly charged. Therefore, adjusting AC conditioned on the inclusion of observed systematic factors could help achieve a more accurate and balanced assessment of capital requirements.

According to the final rule of the Enterprise Regulatory Capital Framework, it seems like the FHFA employs a bank-like standard for GSEs where the core capital should be at least 8 percent of risk-weighted assets (RWA) or at least 2.5 percent of the adjusted total assets. By the end of 2022, the required capital required for both GSEs is approximately 316 billion.[35] Meanwhile, the latest stress test released for 2022 indicates that the maximum credit losses GSEs would suffer in adverse conditions is 16.8 billion.[36] This implies that the total required capital is almost 19 times greater than the calculated loss. Our analysis indicates that with an adjusted total asset of 8.2 billion, the estimated capital level could range from 131 billion (for the +Macro Model) to 164 billion (for the Origination Model). This is approximately 8 to 10 times greater than the recent expected loss from stress test models. This calculation may require further refinement from domain experts. Interestingly, the latter is aligned with the industry expectation and the recent stress test outcomes from GSEs (Layton, 2023).[37]

In short, the degree of incorporating macroeconomic conditions into the PD models could increase the procyclicality problem in capital requirement. However, this could be mitigated if our proposed unified framework is adopted to assess the systematic risk level and calculate capital requirements. We favor the option of including both local and countrywide systematic shocks, as this leads to a lower degree of procyclicality. If the FHFA opts for a more flexible framework for GSEs to estimate the capital constituent—AC—we could expect lower

[35] https://www.fanniemae.com/media/46441/display

https://www.freddiemac.com/investors/docs/ERCF_Public_Disclosure.pdf

The total RWA on 30th June 2022 is 2.2 trillion, while the adjusted total assets are 8.2 trillion. Total capital ratio is required to be 8% with respect to the RWA. Total capital buffer is 1.36% with respect to adjusted total assets.

[36] https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/Final_2022-Public-Disclosures-FHFA_SA.pdf

[37] The current required capital level for both Fannie Mae and Freddie Mac is reported to be 320 billion, which represents a significant increase compared to the loss incurred during the stress test (i.e., 5 billion) by a factor of 60, and a five-fold increase from their combined capital level in 2009. Layton (2023)'s estimate ranges from 120 to 135 billion.

capital requirements, allowing GSEs to optimize their overall performance.

There could be differing opinions on the level of capital requirements for GSEs. Some argue for high levels to ensure financial stability and some for low levels due to the role of government (Bernanke, 2007; Richardson et al., 2017). Note that this chapter focuses on minimum capital requirements. The final decision on capital buffers for GSEs may be introduced in consultation with stakeholders. Our results may be scaled up or down by adjusting the safety level (we chose 99.9 percent in line with Basel standards). Capital buffers play an important role towards minimum capital levels for commercial banks. However, the role of capital buffers is perhaps less important for GSEs than for commercial banks as the ultimate shareholder is the government and should in theory be in a position to cover any shortfalls below the minimum capital at all times.

2.5.3.2 Subsample analysis—heterogeneity across mortgages

To estimate the two-factor CPD models, we assumed that mortgages are homogenous. Although all mortgages in our sample are securitized and GSE-eligible, it is still arguable that they exhibit different exposures to systematic risk due to the preference of originators (i.e., banks vs. nonbanks), the recourse laws (nonrecourse states vs. recourse states), and the state level's housing risk (California vs. other states).[38] These subsample analyses are counterfactual but informative to GSEs, as they could have a more appropriate securitization policy for different types of loans to reflect the systematic risk levels. We now implement the estimation for multiple subsamples to examine whether different groups of loans have different exposures to systematic risk factors. We present the estimations in Table 2.7. Three panels in this table present the following results: Panel A analyzes banks and nonbank subsamples, Panel B analyzes recourse and nonrecourse subsamples, and Panel C analyzes California and other state

[38] According to Cotter et al. (2015), the housing risk of California is substantially higher than other states.

subsamples.[39] In each panel, we report the estimates of Beta, AC, and max-min variations in mean PD, regulatory and economic WCDR, and maximum capital ratio.

We observe a strong result consistency between the full sample and subsample analyses, including the increasing Betas and decreasing ACs. The results of max-min variations in mean PD and WCDR, and maximum capital ratio are also highly consistent with the main analysis. These findings confirm the complementary roles of unobserved and observed systematic risk factors in explaining the total systematic variations. Properly incorporating macroeconomic conditions in capital requirements can contribute to procyclicality, assuming that GSEs adhere to the current Basel framework. This is evidenced by the wider gaps between the maximum and minimum values of mean PD and regulatory WCDR. However, our findings consistently demonstrate that adopting a unified framework leads to reduced cyclicality of capital requirements across all subsamples. Both the Max-Min difference in WCDR and the capital ratios calculated under the unified framework are lower compared to those under the Basel framework. Among the three models examined, the +Macro Model proves to be the most effective. These findings reinforce that allowing for adjustable AC in the capital equation contributes to a reduction in economic capital and promotes a more efficient allocation of capital.

Lender types

We analyzed the systematic risk levels in mortgages originated by bank and nonbank lenders.[40] Nonbank lenders have stronger exposures to both observed and unobserved factors,

[39] We further implement more granular analyses at the region level or risk classes and present the results in the Internet Appendix 2.B and 2.C respectively. For the risk classes, we form 10 classes with the same number of default events. Mortgages in the lowest-risk group dominate the portfolio and have the lowest default rate. Those in the higher-risk group are less common; hence resulting in a higher default rate.

[40] Banks are defined as depository institutions including credit unions and savings associations. Nonbanks are mainly mortgage companies. Other nonbank lenders can be unregulated subsidiaries of bank holding companies, finance companies, or investment trusts. We check the description of their business lines on Bloomberg/their website/SEC to decide whether the lenders are bank or nonbank. We have 68 nonbank lenders and 38 traditional banks in our sample.

which are indicated by higher Beta and AC for nonbank lenders in all three models. The findings could be explained by two reasons. First, nonbanks hold a more homogeneous portfolio than banks. The Herfindahl-Hirschman indexes based on core loan characteristics such as FICO, LTV, and DTI are higher for nonbank lenders than traditional banks.[41] This reveals that nonbank loan portfolios are narrower and more concentrated than banks. In other words, nonbank lenders' loan portfolios are more homogeneous, and individual loans' risks are likely to co-move if exposed to systematic shocks. Second, nonbank lenders rely heavily on securitization to support their businesses, so they tend to strictly follow securitization eligibility to originate the conforming loans to maintain liquidity (Kim et al., 2018). This results in more homogeneous originations and, hence, greater systematic risk. Further, the study of Demyanyk and Loutskina (2016) showed that nonbank lenders originate mortgages to riskier borrowers than bank lenders. Irani et al. (2021) explained that nonbank lenders are under less regulatory oversight. As a result, nonbank mortgages may be more sensitive to systematic risk, as Hilscher and Wilson (2017) show it increases with unconditional risk.

The average capital ratios estimated for both banks and nonbanks are the same at 1.7 percent across all three models. This suggests that GSEs perceive mortgages in a homogeneous manner across various lenders, despite the likelihood of nonbank lenders carrying higher exposure to systematic risk.

Recourse types

Next, we investigate the systematic risk levels of mortgages originating in recourse and nonrecourse states. Recourse lenders have access to collateralizing house and general borrower assets. Hence, borrowers tend to default if they encounter negative equity and liquidity constraints. Nonrecourse lenders only have access to the collateralizing house, so borrowers

[41] FICO-related HHI is 1000.78 for nonbank lenders and 1000.57 for banks. LTV-related HHI is 1352.61 for nonbank lenders and 1417.70 for banks. DTI-related HHI is 1018.28 for nonbank lenders and 1008.21 for banks. Higher HHI values indicate a higher degree of concentration.

may default if they experience negative equity. Nonrecourse mortgages potentially have a higher systematic risk level than recourse mortgages, as the defaults are more driven by systematic risk in relation to housing markets (Cotter et al., 2015).

Our results show that in all three models, Beta and AC of mortgages in nonrecourse states are higher than those in recourse states. As a result, the total systematic risk levels of nonrecourse mortgages are greater than those of recourse mortgages. Ghent and Kudlyak (2011) and Elul et al. (2023) demonstrates that recourse law to general borrower assets lowers the sensitivity to house price drops and hence the likelihood of strategic default. This effect curtails the co-movements of default events and reduces systematic risk.

In terms of capital charges, the average capital ratio across three models is 1.5 percent for recourse mortgages and 2 percent for nonrecourse ones. This result suggests that GSEs should consider incorporating the propensity for strategic default among nonrecourse borrowers when developing their capital frameworks.

States

We continue estimating exposure to systematic risk at the state level, as the various state-related macroeconomies may exert various impacts on systematic default risk. Cotter et al. (2015) find that California's housing market is particularly exposed to greater systematic risk than other states. To simplify, we group mortgages originating from states other than California and implement the comparative analysis on systematic risk levels between California and other states.[42]

We find that the estimations of Beta and AC are markedly higher for California than for other states, which is strongly consistent to Cotter et al. (2015). The total systematic risk for California is almost double that of other states. Our finding can be explained by two-fold: First,

[42] We also adopted Cotter et al. (2015)'s regional category and estimate the systematic risk levels at regional level. The results consistently showed that mortgages in California are more likely to be exposed to systematic risk and have a higher systematic risk level for both Beta and AC. We presented the results in the Internet Appendix 2.B.

asset correlation for the housing market in California is higher than other states; and second, California is a nonrecourse state, so their mortgages are more sensitive to systematic risk factors, as argued above. Note that the systematic risk of California is greater than the one for all nonrecourse states.

We also obtain different capital ratios for mortgages across states with 2.2 percent for California mortgage and 1.6 percent for other states. This finding highlights the presence of regional heterogeneity as a significant factor to consider in the risk-based capital framework of GSEs.

In short, the subsample analyses show the interesting findings that loans originating from nonbank lenders located in nonrecourse states and California tend to have higher exposure to systematic risk. We highly recommend that regulators take these heterogeneity patterns into consideration for a more accurate risk management framework. Given the dominant presence of nonbank lenders in the mortgage landscape, it is crucial to ensure that they are included and accounted for in regulatory measures.

Table 2.7: Systematic risk levels for sub-samples (Stage 3)

Note: This table presents the estimates of Beta and AC for different types of lenders (banks vs. non-bank lenders) in Panel A, different types of judicial systems (recourse vs. non-recourse laws) in Panel B, and for different states (CA vs. other states). Beta and AC are estimated as specified in Eq. (2.25) and Eq. (2.26) for each sub-sample. The dependent variable is the default rate by year of each sub-sample. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD models as the proxy of observed systematic risk factor. Unobserved factors are proxied by a set of time (year) dummies. We report the standard errors in parentheses. ***, **, * indicate the confidence level at 1%, 5% and 10% respectively. We also calculate the Max-Min differences in mean PD, WCDR under both Basel and unified framework, and maximum capital ratio for each subsample. Basel's WCDR is calculated with the regulatory value of AC, which is 15 percent, according to Basel. The WCDR under the unified framework is calculated using the estimated ACs.

Panel A: Banks vs. Non-bank institutions

	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
	Bank			Non-bank		
Beta	0.010	0.045***	0.049***	0.008	0.049***	0.056***
	(0.007)	(0.006)	(0.005)	(0.007)	(0.008)	(0.006)
AC	0.032***	0.004***	0.002***	0.04***	0.006***	0.003***
	(0.01)	(0.001)	(0.001)	(0.012)	(0.002)	(0.001)
Total	0.042***	0.049***	0.051***	0.048***	0.056***	0.059***
	(0.012)	(0.006)	(0.005)	(0.014)	(0.008)	(0.006)
$\Delta_{\text{Max-Min}}$ in Mean PD	0.007	0.019	0.019	0.008	0.022	0.022
$\Delta_{\text{Max-Min}}$ in WCDR, Basel	0.064	0.149	0.148	0.071	0.157	0.162
$\Delta_{\text{Max-Min}}$ in WCDR, Unified	0.023	0.029	0.026	0.028	0.037	0.033
Maximum capital ratio	0.017	0.015	0.014	0.022	0.020	0.018

Panel B: Recourse states vs. Non-recourse states

	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
	Recourse states			Non-recourse states		
Beta	0.008	0.043***	0.048***	0.011	0.056***	0.06***
	(0.006)	(0.006)	(0.005)	(0.008)	(0.007)	(0.005)
AC	0.032***	0.005***	0.003***	0.04***	0.005***	0.002***
	(0.01)	(0.001)	(0.001)	(0.012)	(0.002)	(0.001)
Total	0.04***	0.047***	0.051***	0.052***	0.061***	0.063***
	(0.011)	(0.006)	(0.005)	(0.015)	(0.008)	(0.005)
$\Delta_{\text{Max-Min}}$ in Mean PD	0.007	0.020	0.021	0.007	0.019	0.018
$\Delta_{\text{Max-Min}}$ in WCDR, Basel	0.067	0.148	0.150	0.065	0.141	0.139
$\Delta_{\text{Max-Min}}$ in WCDR, Unified	0.024	0.032	0.029	0.026	0.030	0.025

Maximum capital ratio	0.018	0.017	0.016	0.020	0.017	0.014

Panel C: California vs. Other states

	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
		Other states			CA	
Beta	0.008	0.043***	0.048***	0.019	0.088***	0.093***
	(0.006)	(0.006)	(0.005)	(0.013)	(0.012)	(0.006)
AC	0.032***	0.004***	0.003***	0.063***	0.008***	0.002***
	(0.01)	(0.001)	(0.001)	(0.019)	(0.003)	(0.001)
Total	0.04***	0.047***	0.05***	0.082***	0.096***	0.095***
	(0.011)	(0.006)	(0.005)	(0.022)	(0.012)	(0.006)
$\Delta_{\text{Max-Min}}$ in Mean PD	0.007	0.019	0.019	0.008	0.022	0.022
$\Delta_{\text{Max-Min}}$ in WCDR, Basel	0.064	0.149	0.148	0.071	0.157	0.162
$\Delta_{\text{Max-Min}}$ in WCDR, Unified	0.023	0.029	0.026	0.028	0.037	0.033
Maximum capital ratio	0.017	0.015	0.014	0.022	0.020	0.018

2.5.4 Pricing impact of systematic risk level

We now investigate to what extent systematic risk can explain loan pricing at origination. Mortgage lending has established loan pricing only at loan origination; hence, later performance-based adjustments of loan prices are uncommon. To create more heterogeneity in systematic risk levels, we randomly split the samples into 10,000-loan portfolios and run the estimations for each subsample. We summarize the estimations in Appendix 2.D.

2.5.4.1 Full sample

We compute the unexpected loss (UL) as the exposure to systematic risk levels, as this is the basis for economic and regulatory capital and hence the funding costs of loans. Note that the cost for the capital-funded part of a loan may be based on the risk-free rate plus a premium that is often explained by the product of market risk premium and beta.[43] The cost of the debt-funded part of a loan may be based on the risk-free rate plus a bank-specific credit spread and is generally lower in relative terms. Using the UL can directly provide economic intuition on how lenders should price systematic risk, as this is the basis for bank capital. We utilize the estimated ACs in the UL calculations, as the findings could possibly reveal the roles of different systematic components in pricing. The UL from the Origination Model could emphasize the influence of unobserved factors, while the UL from the +Macro Model could highlight the role of observed factors.

Table 2.8 reports the pricing results with the measurements of unexpected loss relative to the regulatory benchmark of 15 percent and the estimated ACs from the two-factor risk model framework.

We find that the unexpected loss based on the two-factor models exerts a stronger impact on mortgage rates than the regulatory framework. The magnitudes of the coefficients on UL are

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[43] Depending on historic time period and geography, market risk premiums are between 2% and 8% p.a. (Dimson et al., 2011). Bank betas may be between 0.5 and 1.08 (see https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/Betas.html).

consistently higher in the two-factor model than in the regulatory model. In terms of economic meaning, a one-percent increase in the regulatory UL leads to an increase of roughly 2 bps in the mortgage rate, while a similar increase in the most comparable UL (i.e., Origination Model) induced by the two-factor risk model leads to a rise of 4 bps in the mortgage rate. This finding demonstrates that our proposed models likely align with lenders' internal risk frameworks. The adoption of an in-house estimation may allow lenders to price mortgages against systematic risk more accurately.

Table 2.8: Pricing results on the full sample (Stage 4)

Note: This table presents the impact of exposure to systematic risk on mortgage interest rates. The exposure is computed as the unexpected loss (UL) as the difference between the VaR and unconditional PD. VaR is calculated using the Mean PDs, estimated ACs from the two-factor risk models, and the conservative systematic risk value (0.999) specified in Basel III. The names of the CPD models are consistent with the PD models as we employ the mean PD from these models. Specifically, the Origination Model for PD is specified in Eq. (2.11); the +Dynamic Model for PD is specified in Eq. (2.12); and the +Macro Model for PD is specified in Eq. (2.13). Rate is the national average rate on 30-year fixed-rate mortgages. We include all loans and borrowers' characteristics, including FICO, original DTI, original LTV, original loan size, and various dummy variables for refinance, multiple borrowers, non-single-family property, third-party origination, mortgage insurance, and investment purpose as control variables. We also include the splines of FICO, DTI, and LTV for their potential nonlinear effects on mortgage rates. State and vintage dummies are also included. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. We also provide the R-square and number of observations for each pricing regression at the bottom of the table.

	Regulatory benchmark	**Origination**	**+Dynamic**	**+Macro**
UL	0.022*** (0.002)	0.042*** (0.005)	0.173*** (0.024)	0.199*** (0.026)
Rate	0.427*** (0.035)	0.417*** (0.035)	0.485*** (0.043)	0.461*** (0.041)
Intercept	0.04*** (0.002)	0.044*** (0.002)	0.048*** (0.003)	0.051*** (0.003)
Control variables	Yes	Yes	Yes	Yes
FICO splines	Yes	Yes	Yes	Yes
DTI splines	Yes	Yes	Yes	Yes
LTV splines	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Vintage FEs	Yes	Yes	Yes	Yes
Lender cluster	Yes	Yes	Yes	Yes
R-square	0.908	0.908	0.909	0.909
No of obs.	20,486,935	20,486,935	18,827,976	18,827,976

We notice that the highest sensitivity is recorded at 20 bps when the UL is calculated with average PD and the corresponding AC from the two-factor model using the +Macro

Model's input. This suggests that only a portion of the costs implied by systematic risk are priced. For example, if the market risk premium is 6 percent and beta 1 percent and the credit spread for debt funding is 2 percent, then a fair price may imply an increase of the mortgage rate of 4 percent for an increase of UL by 1 percent. The current regulatory framework may not align well with the lenders' internal risk management practices due to procyclicality concerns, but we propose that transitioning to a model that properly incorporates macroeconomic conditions is expected to enhance the efficiency of the pricing scheme.

We also find that the sensitivity of mortgage rates to the estimated systematic risk also increases monotonically from the Origination to the +Macro Model. Sensitivity significantly increases after we start controlling for macroeconomic conditions. We do not decompose the contribution of each systematic risk factor, as both factors are complementary. However, the increase in sensitivity across the three models could imply a stronger force from the observed systematic risk factor. Therefore, an incorporation of the observed systematic risk factor would also be beneficial to GSEs as it would exert greater risk management control over securitization policies and tolerances when purchasing mortgages from lenders. This could then lead to more precise pricing models, and we hypothesize that the accuracy of the model increases as systematic risk is priced to a greater extent as mortgage markets and competition in these increase over time.

2.5.4.2 Subsamples

Next, we present the pricing results for different subsamples, including bank lenders and nonbank lenders (Panel A), nonrecourse states and recourse states (Panel B), and CA and other states (Panel C) in Table 2.9. As we explore and find that systematic risk levels are significantly different among different groups of mortgages, this pricing analysis explains whether mortgages are priced heterogeneously in different competition environments and regions.

Table 2.9: Pricing results for sub-samples (Stage 4)

Note: This table presents the impact of exposure to systematic risk on mortgage interest rates for different subsamples. The exposure is computed as the unexpected loss (UL) as the difference between the VaR and unconditional PD. VaR is calculated using the Mean PDs and estimated ACs from the two-factor risk models and the conservative systematic risk value (0.999) as specified in Basel III. The names of the CPD models are consistent with the PD models as we employ the mean PD from these models. Specifically, the Origination Model for PD is specified in Eq. (2.11); the +Dynamic Model for PD is specified in Eq. (2.12); and the +Macro Model for PD is specified in Eq. (2.13). Rate is the national average rate on 30-year fixed-rate mortgages. We include all loans and borrowers' characteristics, including FICO, original DTI, original LTV, original loan size, and various dummy variables for refinance, multiple borrowers, non-single-family property, third-party origination, mortgage insurance, and investment purpose as control variables. We also include the splines of FICO, DTI, and LTV for their potential nonlinear effects on mortgage rates. State and vintage dummies are also included. Panel A shows the pricing results for banks and non-bank lenders. Panel B shows the pricing results for recourse and non-recourse states. Panel C shows the pricing results for California and other states. Standard errors are clustered by the lender to control lending standards and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. We also provide the R-square and number of observations for each pricing regression at the bottom of each panel.

Panel A	**Banks**			**Non-bank lenders**		
	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
UL	0.048***	0.169***	0.153***	0.037***	0.118***	0.092***
	(0.008)	(0.034)	(0.03)	(0.005)	(0.021)	(0.015)
Rate	0.47***	0.535***	0.499***	0.347***	0.402***	0.367***
	(0.037)	(0.057)	(0.048)	(0.029)	(0.032)	(0.033)
Intercept	0.043***	0.048***	0.052***	0.047***	0.051***	0.055***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
FICO, DTI, LTV splines	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender cluster	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.904	0.906	0.906	0.908	0.910	0.910
No of obs.	10,881,888	10,032,793	10,032,793	9,605,047	8,795,183	8,795,183
Panel B	**Recourse states**			**Non-recourse states**		
	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
UL	0.044***	0.125***	0.116***	0.038***	0.098***	0.105***
	(0.006)	(0.018)	(0.018)	(0.003)	(0.013)	(0.012)
Rate	0.423***	0.473***	0.442***	0.404***	0.447***	0.42***
	(0.033)	(0.039)	(0.037)	(0.04)	(0.047)	(0.045)

Intercept	0.044*** (0.002)	0.051*** (0.003)	0.055*** (0.003)	0.046*** (0.003)	0.052*** (0.003)	0.055*** (0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
FICO, DTI, LTV splines	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender cluster	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.908	0.910	0.910	0.907	0.909	0.909
No of obs	13,021,487	11,962,322	11,962,322	7,465,448	6,865,654	6,865,654

Panel C		**Other states**			**California**	
	Origination	**+Dynamic**	**+Macro**	**Origination**	**+Dynamic**	**+Macro**
UL	0.048*** (0.006)	0.2*** (0.028)	0.228*** (0.03)	0.02*** (0.001)	0.09*** (0.013)	0.118*** (0.016)
Rate	0.423*** (0.034)	0.497*** (0.043)	0.475*** (0.042)	0.375*** (0.041)	0.432*** (0.05)	0.415*** (0.047)
Intercept	0.044*** (0.002)	0.048*** (0.003)	0.051*** (0.003)	0.043*** (0.003)	0.044*** (0.003)	0.046*** (0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
FICO, DTI, LTV splines	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender cluster	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.907	0.909	0.909	0.912	0.914	0.914
No of obs	17,804,004	16,372,652	16,372,652	2,682,931	2,455,324	2,455,324

The coefficients on the UL are positive and significant at the 1 percent level in all pricing regressions relative to different subsamples, indicating that mortgage rates are priced differently across types of lenders, types of recourse laws, and states. Again, the coefficient magnitudes from the regressions related to the Dynamic and +Macro Models are higher than those from the Origination Model. These findings reinforce the idea that incorporating more observed systematic factors captured by the proxies of macroeconomic conditions could help achieve a more efficient pricing scheme.

Our findings exhibit a heterogeneity in the sensitivity of mortgage rates to systematic risk. We find that banks, lenders at recourse states, and those located in states other than California require a higher price for systematic risk, although our prior findings demonstrate that these groups of mortgages are less risky in terms of systematic risk levels. The rational outcome should be that lower-risk mortgages carry a lower rate. This result could be induced by the uniform pricing strategy documented in Heitfield (1999) and Park and Pennacchi (2009). They observed similar prices across bank branches and even across different lenders because of an efficient and competitive market. This uniform pricing strategy leads lenders to charge higher prices for lower-risk mortgages and lower prices for higher-risk mortgages. As a result, the former category exhibited greater sensitivity to systematic risk, while the latter category demonstrated lower sensitivity to systematic risk.

2.5.5 Robustness tests

In this section, we conducted three additional tests. First, we used the first principal component obtained from the state-year panel PD estimations as the proxy for the observed systematic risk factor. While mean PD captures the general tendency of PD over time, the first principal component represents the direction of maximum variations in PD. Both proxies could reflect the effect of observed systematic risk. Second, we used the pooled two-stage logit model to estimate the PDs. While the rolling approach we employ for the main analysis could effectively reduce hindsight bias, the implementation requires a larger data set to produce unbiased estimations. If the portfolio is small, estimating PDs using pooled logit regression could be more reasonable. Third, we undergo the robustness test using an alternative method to estimate PD: multinomial logit model. This method has become quite popular in recent literature and helps control the competing bias between default and prepayment.

2.5.5.1 Using the first principal component as the proxy for the observed systematic risk factor

We calculate the average default probability by state-year and then extract the first principal component (PC1) from a panel consisting of 52 states and 21 years. Before replicating the regression of the CPD model in Eq. (2.17) and estimating the systematic risk levels, we standardized PC1 to allow for the magnitude comparison between beta and AC. We summarize the results in Panel A of Table 2.10. The results are strongly consistent with our main finding in terms of magnitude and significance. This confirms the negative association of beta and AC, implying the intercorrelation between observed and unobserved systematic risk factors in driving default clustering.

2.5.5.2 Using the pooled two-stage logit model to estimate mean PD

The results from this test are consistent with the main analysis in terms of the sign and significance level, but the estimation magnitudes are slightly larger than those presented in Section 5. This is because the default variations from the pooled sample are likely larger than the rolling subsamples; hence, the exposures to systematic risk factors are also larger.[44] Nevertheless, these findings confirm our findings and reinforce the importance of controlling macroeconomic conditions and incorporating observed systematic risk factors in deriving capital requirements.

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[44] We provide the results using the pooled two-stage logit regressions and defining default as foreclosure events only in the Internet Appendix 2.E. Panel 1 presents the regression outcomes of PP models, Panel 2 presents the regression outcomes of PD models, and Panel 3 presents the estimations of systematic risk levels including Beta, AC and Total systematic risk. The results are strongly consistent with the main analysis.

Table 2.10: Robustness tests

Note: This table shows the results from robustness tests. Panel A shows the estimates of systematic risk levels when the proxy for the proxy of the observed systematic risk factor is the first principal component obtained from the state-year PD panel. Panel B shows the estimates of systematic risk levels when Mean PD is drawn from PD models estimated using the pooled two-stage logit model. Panel C shows the estimates for systematic risk levels when Mean PD is obtained from PD models estimated by the multinomial logit model. In each panel, we present the estimations of Beta, AC, and Total systematic risk. Standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

Panel A: The first principal component as the proxy for the observed factor			
	Origination	**+Dynamic**	**+Macro**
	0.009	0.046***	0.052***
Beta	(0.007)	(0.007)	(0.005)
	0.034***	0.006***	0.002***
AC	(0.01)	(0.002)	(0.001)
	0.043***	0.051***	0.054***
Total systematic risk	(0.012)	(0.008)	(0.005)
Panel B: Pooled two-stage logit model to estimate Mean PD			
	Origination	**+Dynamic**	**+Macro**
Beta	0.023	0.058***	0.064***
	(0.017)	(0.017)	(0.016)
AC	0.057***	0.025***	0.021***
	(0.017)	(0.007)	(0.006)
Total systematic risk	0.079***	0.082***	0.085***
	(0.023)	(0.018)	(0.017)
Panel C: Multinomial logit model to estimate Mean PD			
	Origination	**+Dynamic**	**+Macro**
	0.029	0.059***	0.062***
Beta	(0.018)	(0.016)	(0.017)
	0.051***	0.023***	0.022***
AC	(0.015)	(0.007)	(0.007)
	0.08***	0.081***	0.084***
Total systematic risk	(0.022)	(0.017)	(0.017)

2.5.5.3 Using multinomial logit model to estimate mean PD

Instead of using two-stage regressions, we employ the multinomial logit model to estimate PD and hence mean PD. This method allows us to estimate PP and PD concurrently, which is recommended to deal with the competing outcomes of mortgages in a specific time period (Heinen et al., 2021; Luong & Scheule, 2022; Pennington-Cross & Chomsisengphet, 2007). The findings presented in Panel B of Table 2.10 confirm the increasing pattern of Beta and the decreasing pattern of AC. The magnitudes of total systematic risk levels are also slightly larger than the main results, as influenced by the pooled sample.

2.6 Regulation and industry impacts

This research paper evaluates different model options based on a unified framework for GSEs' potential risk-based capital framework, which will be applied from 2025. The unified framework incorporates both observed and unobserved systematic risk factors, in which the former captures the effect of observable macroeconomic conditions, and the latter reflects other unobservable impacts of the economic cycle. From this framework, we establish three models differing in the level of observed factor and estimate the systematic risk level, AC—as a capital constituent. Our analysis indicates that the inclusion of observed systematic risk factors dominates and outweighs the traditional latent systematic risk factor in driving systematic risk variations, leading to a lower AC.

The analysis of level and capital cyclicality reveals that the inclusion of observed factor causes the increase in cyclicality of capital requirement. However, this effect can be counterbalanced by the decreasing AC produced from the unified framework, demonstrating a reduction in the procyclicality in capital managements. Additionally, utilizing this framework leads to more reasonable capital charges compared to the Basel requirement. In a nutshell, the capital ratio under the unified framework is 2 percent while that under the Basel is 6.7 percent. With the total assets of 8.2 trillion for both Fannie Mae and Freddie Mac, the economic capital is supposed to be 164 billion. Interestingly, this figure meets the industry expectation and is also consistent with the recent GSE stress test results. The unified framework also helps improve the mortgage pricing scheme as it allows to capture higher sensitivity of mortgage rate to systematic risk. We also find meaningful differences in the exposures to systematic risk factors across types of lenders, types of recourse laws, and states.

The internal model-based framework with a combination of both systematic risk factors holds the potential for better alignment with lenders' risk management practices and lower capital requirements. This alignment not only enhances the efficiency of capital allocation but also improves the accuracy of pricing schemes. Considering these benefits, GSEs may find value in adopting the unified framework as a more optimized approach to measuring systematic risk.

Among the various models analyzed, we advocate for the adoption of the most comprehensive model, known as the "+Macro Model". This model captures observed systematic risk comprehensively by incorporating both local and nationwide shocks. As a result, it yields the lowest capital charges and exhibits the highest sensitivity to mortgage rates. While the +Macro Model introduces a marginal increase in the cyclicality of capital requirements, its overall advantages outweigh this factor.

By embracing a more comprehensive approach to risk measurement, policymakers can enhance the effectiveness of risk management frameworks and promote a more resilient and stable financial system. Our research findings can also assist policymakers in terms of minimizing and adapting to a higher levels of risk granularity. GSEs securitization activities and bank lending are linked as GSEs play a significant role in providing liquidity for mortgage markets and influencing lending dynamics. Changes in GSE securitization standards cause changes in lending standards. For example, a loosening (tightening) of GSE securitization standards during economic upturns (downturns) may lead to a loosening (tightening) of lending standards.

GSE lending procyclicality may therefore lead to lending pro-cyclicality, which may challenge GSEs' missions to stabilize the financial system. We see this risk as limited as firstly our results show that the dynamic model results in lower capital requirements and second, governments can assist by supplying additional capital. As a fact, both Fannie Mae and Freddie Mac faced significant difficulties and had to be placed under government conservatorship during the 2008 crisis, leading to a curtail in their securitization activities. This provided an additional macroprudential tool (perhaps managed by the independent FHFA) next to monetary policy by the Federal Reserve Bank. This aspect may prove critical and warrant further research and debate.

Appendix 2.A: Literature review on systematic risk

Note: This table summarizes the literature review on systematic risk. Stream 1 refers to studies estimating the impacts of systematic risk factors, but do not estimate the systematic risk levels. Stream 2 refers to those estimating systematic risk levels explicitly.

Paper	Region	Period	Model	Asset class	Observed factor	Latent factor	Stream
Our paper	US	1999–2019	Nonlinear mixed model	Mortgage	Yes	Yes	2
Lee et al. (2021)	US	2002–2014	State space	Mortgage	No	Yes	2
Calem and Follain (2003)	US	1982–2000	Survival model	Mortgage	No	Yes	2
Gupta (2019)	US	2000–2010	IV regression	Mortgage	Yes	No	1
Goodstein et al. (2017)	US	2005–2009	Logit	Mortgage	Yes	No	1
Amromin and Paulson (2009)	US	2004–2007	Probit	Mortgage	Yes	No	1
Elul et al. (2010)	US	2005–2009	Logit	Mortgage	Yes	No	1
Calabrese and Crook (2020)	UK	2006–2015	Spatial generalized extreme value survival model	Mortgage	Yes	No	1
Leow and Crook (2016)	UK	2002–2011	Logit	Mortgage	Yes	No	1
Hashimoto (2009)	Japan	1985–2005	Ordered probit model	Corporate	No	Yes	2
Jiménez and Mencía (2009)	Spain	1984–2006	Vector autoregression (VAR)	Corporate	Yes	Yes	1
Azizpour et al. (2018)	US	1970–2012	Method of maximum likelihood	Corporate	Yes	Yes	1
Hilscher and Wilson (2017)	US	1986–2013	Dynamic logit model for Failure score OLS for failure Beta	Corporate	Yes	No	2
Nickerson and Griffin (2017)	US	2000–2007	Joint model estimated by MLE	Corporate	Yes	Yes	1
Duffie et al. (2009)	US	1979–2004	Autoregressive Gaussian time-series model	Corporate	No	Yes	1
Dietsch and	France	1995–	Probit ordered	Corporate	No	Yes	1

Petey (2004)	and Germany	2001	model				
Koopman et al. (2012)	US	1981–2005	Logit	Corporate	Yes	Yes	1
Duffie et al. (2007)	US	1980–2004	Double stochastic model with joint MLE	Corporate	Yes	No	1
Das et al. (2007)	US	1979–2004	Doubly stochastic model	Corporate	Yes	No	1
Pesaran et al. (2006)	US	1987–2003	Global vector autoregressive macroeconomic model	Corporate	Yes	No	1

Appendix 2.B: Systematic risk levels for regional sample

We adopt Cotter et al. (2015)'s categorization and compare our estimates with their results. Our measures would be perfectly correlated to theirs if house prices were the only systematic risk driver. We find that there is a strong association between the total systematic risk in our paper and the housing risk in Cotter et al. (2015), as the correlation is approximately 60 percent across three models. The correlation is the strongest for the Origination Model and the weakest for the +Macro Model. As the correlation between our Origination Model and their model is the highest, this may imply that the housing correlation only represents the unobserved systematic factor and may not capture the impact of observed counterpart. That is the reason why the correlation between our results and their results drops when we incorporate more observed factors into the model.

Looking at systematic risk components across regions, we observe that mortgages in California have substantially higher exposure to systematic risk factors than those in other regions. In the Origination Model, where we do not control the observed factor, the AC estimate reaches the highest level at 6.5 percent. In the +Dynamic and +Macro Models, the Beta estimates for California are also the highest value. This result is greatly consistent to Cotter et al. (2015), which they find that the house price risk in CA is also the highest at 77 percent. Mortgages in California have much higher systematic risk than in other regions, which is likely induced by housing market risk.

For other regions, we find a similar pattern where the contribution of Beta in total systematic risk is higher than that of AC.

Systematic risk levels across different regions (Stage 3)

Note: This table presents the estimation results of Beta, AC, and total systematic risk for CA and nine regions. The Pacific region includes the states AK HI OR WA, the Mountain region includes AZ CO ID MT NM NV UT WY, West North Central (WNC) region includes IA KS MN MO ND NE SD, West South Central (WSC) region includes AR LA OK TX, East North Central (ENC) region includes IL IN MI OH WI, East South Central (ESC) region includes AL KY MS TN, South Atlantic region includes DC DE FL GA MD NC SC VA WV, Middle Atlantic region includes NJ NY PA and New England region includes CT MA ME NH RI VT. Beta and AC are estimated based on Eq. (2.25) and Eq. (2.26) for each region. The dependent variable is the default rate by year of each region. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD models as the proxy of observed systematic risk factor. Unobserved factors are proxied by the set of time (year) dummies. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels, respectively. The last column reports the house price correlation found in Cotter et al. (2015)'s paper to compare with our estimates. The last row shows the correlation between our estimates (total systematic risk) from Cotter et al. (2015) as a benchmark.

	Origination Model			**+Dynamic Model**			**+Macro Model**			**Cotter et al. (2015)**
	Beta	**AC**	**Total**	**Beta**	**AC**	**Total**	**Beta**	**AC**	**Total**	
California	0.021 (0.014)	0.065*** (0.019)	0.087*** (0.024)	0.089*** (0.012)	0.008*** (0.003)	0.097*** (0.012)	0.094*** (0.006)	0.002*** (0.001)	0.096*** (0.006)	0.77
Pacific	0.016* (0.009)	0.032*** (0.01)	0.048*** (0.013)	0.053*** (0.003)	0.001*** (0)	0.054*** (0.003)	0.056*** (0.007)	0.004*** (0.001)	0.06*** (0.007)	0.44
Mountain	0.019 (0.013)	0.057*** (0.017)	0.076*** (0.021)	0.081*** (0.009)	0.005*** (0.002)	0.085*** (0.009)	0.088*** (0.009)	0.004*** (0.001)	0.092*** (0.009)	0.41
WNC	0.006 (0.005)	0.028*** (0.008)	0.034*** (0.01)	0.035*** (0.005)	0.003*** (0.001)	0.039*** (0.005)	0.041*** (0.006)	0.003*** (0.001)	0.045*** (0.006)	0.27
WSC	0 (0.001)	0.013*** (0.004)	0.014*** (0.004)	0.011*** (0.004)	0.005*** (0.002)	0.016*** (0.004)	0.015*** (0.002)	0.001*** (0)	0.016*** (0.002)	0.22
ENC	0.007 (0.006)	0.037*** (0.011)	0.044*** (0.013)	0.045*** (0.007)	0.005*** (0.002)	0.05*** (0.007)	0.052*** (0.007)	0.004*** (0.001)	0.056*** (0.007)	0.39
ESC	0.002 (0.003)	0.025*** (0.008)	0.027*** (0.008)	0.026*** (0.005)	0.005*** (0.001)	0.031*** (0.005)	0.032*** (0.004)	0.003*** (0.001)	0.034*** (0.004)	0.38
South Atlantic	0.014 (0.009)	0.042*** (0.013)	0.056*** (0.016)	0.057*** (0.009)	0.007*** (0.002)	0.063*** (0.009)	0.063*** (0.005)	0.002*** (0.001)	0.065*** (0.006)	0.34
Middle Atlantic	0.012** (0.005)	0.016*** (0.005)	0.028*** (0.007)	0.029*** (0.002)	0.001*** (0)	0.03*** (0.002)	0.03*** (0.003)	0.001*** (0)	0.031*** (0.003)	0.39
New England	0.012 (0.007)	0.028*** (0.009)	0.04*** (0.011)	0.042*** (0.005)	0.003*** (0.001)	0.045*** (0.005)	0.045*** (0.004)	0.001*** (0)	0.046*** (0.004)	0.69
Correlation with Cotter et al. (2015)' result		0.608			0.599			0.556		

Appendix 2.C: Systematic risk levels for risk classes

We estimate the systematic risk level for different risk classes. The risk classes are defined based on the average probabilities of default of each loan. We ensure that the number of default events is comparable between risk classes, so the default rates converge to conditional default probabilities. Hence, the first class has the most observations and the lowest default rate, while the last class has the least observations and the highest default rate. Panel C1 shows the number of observations and default rate (in percentage) for each risk class, and Panel C2 shows the estimations of systematic risk levels for each risk class across three models.

We find that Beta estimates are not statistically significant throughout the classes in the Origination Model, leaving AC as the sole contributor to the total systematic risk. In the +Dynamic Model, the contributions of Beta and AC are mostly comparable, but the driving force of AC tends to be stronger than Beta for higher-risk mortgages. Regarding the +Macro Model, Beta outweighs AC in forming total systematic risk.

We further notice that Beta and AC likely increase from the lowest to the highest-risk class, indicating that higher-risk mortgages have greater exposure to systematic risk factors than lower-risk mortgages. In the +Macro Model, for example, Beta estimates rise from 0.001 to nearly 0.084, and AC estimates increase from 0.003 to roughly 0.049. Higher-risk mortgages are more exposed to systematic risk factors than lower-risk mortgages. This finding is consistent with Hilscher and Wilson (2017). While the unified framework may result in overall capital reductions, these reductions are distributed across all portfolios. Higher-risk borrowers still demand higher capital requirements in comparison to lower-risk groups.

Calem and Follain (2003) suggest applying 15 percent for systematic risk levels in mortgages on single-family residences, which the Basel regulations have adopted. Our analysis indicates that it may be more reasonable to use lower and different systematic risk levels for various mortgages based on their distinctive levels of risk. Consequently, more suitable capital levels may be derived to absorb potential loan losses.

Panel C1: Risk class formation

Note: This table describes the risk classes based on the unconditional PDs from the Origination Model specified in Eq. (2.11), the +Dynamic Model specified in Eq. (2.12), and the +Macro Model specified in Eq. (2.13). Classes have equal numbers of default observations. Moving from the lowest-risk to the highest-risk classes, the number of observations demonstrates a decreasing pattern, while the default rate shows an increasing pattern.

	Origination		**+Dynamic**		**+Macro**	
	No of obs.	Default rate	No of obs.	Default rate	No of obs.	Default rate
Lowest risk	37,292,449	0.002	52,195,264	0.002	53,429,090	0.002
2	16,930,870	0.005	15,369,237	0.006	15,298,613	0.006
3	12,057,032	0.007	9,051,254	0.009	8,957,069	0.009
4	9,221,735	0.009	6,205,134	0.014	6,107,337	0.014
5	7,291,329	0.012	4,664,782	0.018	4,566,454	0.019
6	5,816,038	0.015	3,704,630	0.023	3,568,868	0.024
7	4,675,391	0.018	3,008,080	0.028	2,876,871	0.029
8	3,715,207	0.023	2,458,575	0.034	2,292,826	0.037
9	2,837,843	0.030	1,979,691	0.043	1,785,004	0.048
Highest risk	2,018,824	0.042	1,427,571	0.059	1,182,086	0.072

Panel C2: Systematic risk levels across risk classes

Note: This table presents the estimates of Beta and AC for different risk classes. Risk classes are categorized based on average PD per loan, and the number of default events in each class is ensured to be comparable. The lowest-risk class consists of mortgages with the lowest PD, and the highest-risk class consists of mortgages with the highest PD. Beta and AC are estimated as specified in Eq. (2.25) and Eq. (2.26) for each risk class. The dependent variable is the number of default events by year of each risk class. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD model as the proxy of observed systematic risk factor. Unobserved factors are proxied by the set of time (year) dummies. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

	Origination Model			**+Dynamic Model**			**+Macro Model**		
	Beta	**AC**	**Total**	**Beta**	**AC**	**Total**	**Beta**	**AC**	**Total**
	0.006	0.027***	0.033***	0.373***	0.581***	0.954***	0.001	0.003***	0.004***
Lowest-risk class	(0.005)	(0.009)	(0.01)	(0.011)	(0.012)	(0.001)	(0.001)	(0.001)	(0.001)
	0.002	0.044***	0.047***	0.363***	0.549***	0.912***	0.003***	0.001***	0.005***
2nd class	(0.004)	(0.014)	(0.014)	(0.011)	(0.011)	(0.005)	(0.001)	(0)	(0.001)
	0.003	0.046***	0.048***	0.387***	0.588***	0.975***	0.008***	0.000**	0.008***
3rd class	(0.004)	(0.014)	(0.015)	(0.012)	(0.012)	(0.001)	(0.001)	(0)	(0.001)
	0.003	0.046***	0.049***	0.362***	0.489***	0.851***	0.014***	0.000**	0.015***
4th class	(0.004)	(0.014)	(0.015)	(0.011)	(0.012)	(0.01)	(0.001)	(0)	(0.001)
	0.003	0.045***	0.048***	0.051*	0.009	0.061	0.022***	0.003***	0.025***
5th class	(0.005)	(0.014)	(0.014)	(0.025)	(0.014)	(0.039)	(0.004)	(0.001)	(0.004)
	0.004	0.043***	0.047***	0.276***	0.568***	0.844***	0.028***	0.007***	0.035***
6th class	(0.005)	(0.013)	(0.014)	(0.015)	(0.009)	(0.014)	(0.006)	(0.002)	(0.007)
	0.004	0.041***	0.045***	0.344***	0.622***	0.965***	0.037***	0.013***	0.05***
7th class	(0.005)	(0.013)	(0.014)	(0.012)	(0.012)	(0.002)	(0.01)	(0.004)	(0.011)
	0.005	0.038***	0.042***	0.36***	0.626***	0.986***	0.044***	0.02***	0.064***
8th class	(0.005)	(0.012)	(0.013)	(0.012)	(0.012)	(0.001)	(0.014)	(0.006)	(0.015)
	0.006	0.036***	0.041***	0.365***	0.626***	0.992***	0.055**	0.035***	0.09***
9th class	(0.006)	(0.011)	(0.012)	(0.012)	(0.012)	(0)	(0.02)	(0.011)	(0.022)
	0.003	0.039***	0.042***	0.361***	0.63***	0.991***	0.084***	0.049***	0.133***
Highest-risk class	(0.004)	(0.012)	(0.013)	(0.012)	(0.012)	(0)	(0.029)	(0.015)	(0.03)

Appendix 2.D: Summary of bootstrapped systematic risk levels

To create more heterogeneity in systematic risk levels for the purpose of testing the pricing impact, we randomly split the sample into 1998 sub-samples and estimated the systematic risk levels for each subsample. For the group analysis, we split the sample into 998 sub-samples as a pair of observations representing each group is concurrently estimated. The following table summarizes the bootstrapped estimations.

Bootstrapped systematic risk levels

Note: This table presents the bootstrapped estimation on systematic risk levels. We randomly form a portfolio of roughly 10,000 loans. With roughly 20 million loans in the sample, we construct 1998 sub-samples. Panel A reports the average systematic risk levels on those sub-samples. For group analysis, we randomly form portfolios with a number of 10,000 mortgages. As a result, we obtain 998 sub-samples.

Panel A: Full sample						
	Origination	+Dynamic	+Macro			
Beta	0.011	0.046	0.046			
AC	0.040	0.005	0.002			
Total	0.051	0.051	0.048			
No of obs.	1998	1998	1998			
Panel B: Bank vs non-bank						
	Origination	+Dynamic	+Macro	Origination	+Dynamic	+Macro
	Bank			Non-bank		
Beta	0.011	0.044	0.042	0.009	0.049	0.048
AC	0.035	0.005	0.001	0.044	0.008	0.003
Total	0.046	0.049	0.043	0.053	0.057	0.052
No of obs.	998	998	998	998	998	998
Panel C: Recourse states vs. Non-recourse states						
	Origination	+Dynamic	+Macro	Origination	+Dynamic	+Macro
	Recourse states			Non-recourse states		
Beta	0.009	0.042	0.040	0.013	0.056	0.052
AC	0.035	0.005	0.001	0.045	0.007	0.001
Total	0.044	0.047	0.041	0.058	0.063	0.054
No of obs.	998	998	998	998	998	998
Panel D: Other states vs. CA						
	Origination	+Dynamic	+Macro	Origination	+Dynamic	+Macro
	Other states			CA		
Beta	0.010	0.042	0.043	0.024	0.088	0.088
AC	0.035	0.005	0.002	0.072	0.012	0.005
Total	0.044	0.047	0.045	0.096	0.101	0.093
No of obs.	998	998	998	998	998	998

Appendix 2.E: Two-stage regression when a default is indicated as foreclosure events

Note: Panel 1 presents the parameter estimates for payoff probabilities (PP). The Origination Model for PP is specified in Eq. (2.6). The +Dynamic Model for PP is specified in Eq. (2.7). The +Macro Model for PP is specified in Eq. (2.8). dependent variable in all models is the payoff indicator. The definitions of explanatory variables are provided in Table 2.1. The coefficients on dummies for origination years are skipped for simplicity. Standard errors are clustered at the state level and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the AUROC, and max rescaled R-square. The number of observations is also provided.

	Origination	**+Dynamic**	**+Macro**
Intercept	-6.414*** (0.258)	-7.691*** (0.237)	-6.577*** (0.188)
FICO	0.001*** (0)	0.001*** (0)	0.001*** (0)
Orig LTV	-0.177*** (0.028)	-0.249*** (0.036)	-0.234*** (0.053)
Orig DTI	-0.11*** (0.012)	-0.003 (0.021)	0.008 (0.022)
Refinance	-0.028*** (0.008)	-0.043*** (0.009)	-0.041*** (0.008)
Multi_borr	0.042*** (0.006)	0.047*** (0.006)	0.047*** (0.004)
Notsf	0.02* (0.012)	0.02 (0.012)	0.02* (0.011)
TPO	0.008 (0.008)	0.001 (0.008)	-0.004 (0.008)
Mgt insurance	-0.019*** (0.006)	-0.015*** (0.005)	-0.022*** (0.007)
Investment	-0.171*** (0.015)	-0.195*** (0.013)	-0.206*** (0.014)
Orig loansize	0.276*** (0.017)	0.31*** (0.017)	0.289*** (0.014)
Interest_rate	0.264*** (0.018)	0.312*** (0.018)	0.313*** (0.017)
LTV_change		-0.192*** (0.049)	-0.28*** (0.087)
DTI_change		0.922*** (0.267)	0.971*** (0.257)
Age		0.24*** (0.006)	0.258*** (0.005)
Age^2		-0.016*** (0)	-0.017*** (0.001)
UER			0.054*** (0.01)
HPI			-0.002*** (0)
Contagion			-14.304*** (2.585)
Vintage dummies	Yes	Yes	Yes
State cluster	Yes	Yes	Yes
AUROC	64.3	70.1	0.715
Max-rescaled R^2	5.75	10.56	12.05
Number of observations	113,182,090	113,182,090	113,182,090

Note: Panel 2 presents the parameter estimates for probabilities of default (PD). The Origination Model for PD is specified in Eq. (2.11). The +Dynamic Model for PD is specified in Eq. (2.12). The +Macro Model for PD is specified in Eq. (2.13). The dependent variable in all models is the default indicator (foreclosure events only). The definitions of explanatory variables are provided in Table 2.1. The coefficients on dummies for origination years are skipped for simplicity. Standard errors are clustered at the state level and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the AUROC, rescaled R-square. The number of observations is also provided.

	Origination	**+Dynamic**	**+Macro**
Intercept	-6.245*** (0.9)	-8.441*** (2.569)	-10.504*** (0.94)
FICO	-0.002*** (0)	-0.002*** (0)	-0.002*** (0)
Orig LTV	1.723*** (0.092)	1.822*** (0.167)	1.775*** (0.095)
Orig DTI	0.488*** (0.042)	0.592*** (0.064)	0.564*** (0.045)
Refinance	0.212*** (0.018)	0.192*** (0.019)	0.178*** (0.011)
Multi_borr	-0.188*** (0.014)	-0.183*** (0.022)	-0.166*** (0.01)
Notsf	0.046 (0.033)	0.02 (0.028)	0.014 (0.012)
TPO	0.063*** (0.012)	0.069*** (0.009)	0.072*** (0.008)
Mgt insurance	-0.027 (0.019)	-0.02 (0.018)	-0.024* (0.013)
Investment	0.042 (0.028)	-0.012 (0.076)	-0.084** (0.038)
Orig loansize	0.122** (0.056)	0.179 (0.143)	0.305*** (0.054)
Interest_rate	0.323*** (0.029)	0.405*** (0.123)	0.521*** (0.052)
LTV_change		0.352 (0.258)	0.095 (0.086)
DTI_change		1.091*** (0.369)	0.892*** (0.19)
Age		0.368*** (0.075)	0.363*** (0.032)
Age^2		-0.021*** (0.005)	-0.02*** (0.002)
UER			0.066*** (0.015)
HPI			-0.001*** (0)
Contagion			0.12** (0.045)
PP	-1.608*** (0.464)	-1.398 (1.27)	-2.743*** (0.6)
Vintage dummies	Yes	Yes	Yes
State cluster	Yes	Yes	Yes
AUROC	86.4	91.7	92.3
Max-rescaled R^2	16.98	25.18	27.54
Number of observations	113,182,090	113,182,090	113,182,090

Note: Panel E3 shows the estimates of systematic risk levels when the default indicator is defined as being involved in foreclosure events only. Standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

	Origination	**+Dynamic**	**+Macro**
Beta	0.039	0.122***	0.117***
	(0.035)	(0.03)	(0.034)
AC	0.148***	0.054***	0.067***
	(0.039)	(0.016)	(0.02)
Total systematic risk	0.188***	0.176***	0.184***
	(0.047)	(0.032)	(0.037)

Appendix 2.F: Downturn LGD

To estimate the Downturn LGD (DLGD), we use the guidelines from the division of banking supervision and regulation of the Fed. We first estimate the expected LGD (ELGD) and then use the following mapping function to calculate DLGD. The ELGD is estimated as follows:

$$\mathrm{ELGD} = \frac{\mathrm{EAD} - \sum_{t=1}^{T}(\mathrm{CF_t}/(1 + \mathrm{r_t})^{t})}{\mathrm{EAD}}$$

Where EAD is the current defaulted balance, CF is the cashflow conditional on the default, r is the discount rate.

The cashflow is the net of inflows and outflows, which is in fact the actual loss. The inflows include the net proceeds from loan sales, mortgage insurance recoveries, non-mortgage-insurance recoveries. The outflows refer to various expenses such as delinquent accrued interest, legal costs, maintenance and preservation costs, taxes and insurance costs, and miscellaneous costs.

For the discount rate, there are several options to choose from such as contract rate, weighted average cost of capital, market return on defaulted bonds, return on equity, or equilibrium returns based on the CAPM model. Contract rate has been commonly used in the literature, but this rate only reflects the interest rate at origination and does not reflect the price for systematic risk (Baesens et al., 2016, p. 278). Despite that, we choose to use the contract rate for convenience.

The equation to compute DLGD is as follows:

$$\mathrm{DLGD} = 0.08 + 0.92 * \mathrm{ELGD}$$

This function follows the guidelines from the Department of the Treasury, Federal Reserve System and Federal Insurance Corporation (2006). Implicit within the guidelines is the rationale that there is a linear relationship between Downturn LGD and Expected LGD (EGLD) with a floor of 8 percent and an upper limit of 100 percent, where the 8 percent is the capital requirement for residential mortgages. We remove ELGD lower than 0 or greater than 1 to control outliers.

Chapter 3 : Personalized contracts for financial resilience in mortgage lending

3.1 Motivation

This paper personalizes mortgage loans by aligning repayments with changes in future borrower income with the aim of improving financial resilience. Currently, fixed-rate mortgages (FRMs) are the dominant contract design in the US,[45] requiring loan amortizations in annuities that include interest and principal repayments. The annuity payments are aligned with borrower income at loan origination to safeguard lenders from costs in relation to borrower liquidity shortfalls. We argue that loan contracts should be personalized as declines in future borrower income can result in systematic defaults.[46]

Evaluating borrower income is crucial for lenders to grasp borrower illiquidity and gauge their risk levels. Ganong and Noel (2022) and Low (2021) have recently found that illiquidity causes 97 percent of mortgage defaults.[47] Borrower income may change over time due to changes in borrower and macroeconomic conditions. Income loss following an economic downturn is an example. One of the solutions is to offer borrowers deferment options. During

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[45] See Center for Microeconomic Data (2021). One of the thesis examiners wonders if this still holds when ARMS are increasing their shares due to the increase in mortgage rates (https://www.corelogic.com/intelligence/rising-rates-lead-to-increase-in-adjustable-rate-mortgage-arm-activity/). According to the article, ARM share has fluctuated between approximately 8 percent to 18 percent of mortgage origination. ARMs are more popular with large loan sizes (i.e., higher than $1 million) with a share of 45 percent. While there may be instances where ARMs gain more popularity in specific market conditions, the overall market share of FRMs remains dominant. The preference for FRMs is due to the value to borrowers to hedge interest rate risks. Lenders are better suited to hedge these risks as they have greater financial sophistication and can bulk hedge for large mortgage portfolios and minimize costs. For ARMs, borrowers face the risk of rising interest rates, which can lead to higher monthly payments and financial uncertainty. Recognizing the increase in ARM share during rising interest rates should not overshadow the enduring appeal and security provided by FRMs for most borrowers in the mortgage market.

[46] During the US foreclosure crisis in 2008, one in 54 households lost their home, house prices dropped nearly 30 percent, and stock markets fell approximately 50 percent as a consequence of illiquidity or leverage (C. Lee, 2009).

[47] The literature has established a double-trigger theory where illiquidity and leverage (or negative equity) are the two critical drivers of mortgage defaults.

the COVID-19 pandemic, a loan value of more than $2 trillion was in forbearance from March to October 2020 under the CARES Act.[48] Another solution is to offer contracts with negative amortization features. This would help borrowers with liquidity constraints to defer payments, but the potential moral hazard limits the implementation in practice and attracts high-risk borrowers. Further consequences are low lending volumes, limited maturities, and high contract rates.

We observe two patterns with regard to anticipated borrower income/circumstances. First, household income tends to grow over time, and the growth rates differ across regions. Second, we find a hump-shaped pattern between loan age and borrower default risk (Figure 3.1), where the risk increases up to year nine since origination and decreases following that.

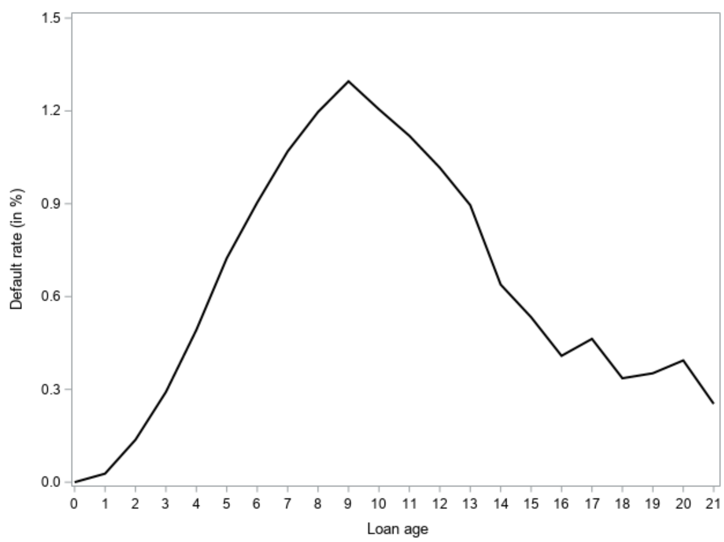

Figure 3.1: Default rate over loan age

Note: This figure shows a hump-shaped pattern between loan age and default rate. The mortgage data is collected from Freddie Mac's public database from January 1999 to December 2019.

This hump-shape age-related risk profile reflect fluctuations in household incomes due

[48] See Cherry et al. (2021)

to borrower life cycles as their default risk could be lessened after year nine.[49] In addition, borrowers are likely more hesitant to default due to a sizeable equity built up in their homes. In this paper, we personalize mortgage contracts ex-ante (i.e., at loan origination) by incorporating these patterns into the repayment schedules. The adjusted repayments intend to lower borrower illiquidity over diversified portfolios and loan lifetimes. Using FRMs as a basis that may allow lenders to achieve large lending volumes, we propose two novel contracts—income-adjusted FRMs (IFRMs) and age-adjusted FRMs (AFRMs). IFRMs integrate borrowers' expected income growth into the repayment schedule,[50] while AFRMs provide a better schedule aimed at neutralizing the adverse effects of age-related risk.

Our key contributions are as follows. First, personalized IFRMs and AFRMs have not been considered in prior literature. We are the first to develop formulas to derive the repayment and loan balance schedules using growing annuities within multiple regimes. The repayments of IFRMs are initially lower than those of FRMs but gradually increase over time, while AFRM repayments decrease from the origination time to year nine and increase thereafter. These formulas are necessary for the industry to operationalize our contracts.

Second, this paper makes a methodological contribution by employing an empirical counterfactual analysis to determine the efficacy of new mortgage designs against traditional ones.[51] We first compute contract-implied proxies for illiquidity and leverage, which are the two critical triggers of mortgage default.[52] The adjusted schedules induce the trade-off effects

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[49] Halket and Vasudev (2014) indicate that most borrowers get their mortgages in their early thirties. Family expansion and expensive childcare and schooling costs could be the main reasons driving the high financial stress in the following years.

[50] We make some simplifying assumptions that involve averaging, and we carefully choose state based as opposed to zip code-based information to ensure fair lending and that borrowers are not discriminated by sociodemographic features of their neighborhoods.

[51] Empirical counterfactual approaches are popular in assessments of new policies. Examples include the multiple quantitative impact studies conducted by the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2021) to evaluate the impact of the Basel regulations prior to implementation.

[52] Illiquidity is commonly measured using the debt-to-income (DTI) ratio, and leverage is proxied through the loan-to-value ratio (LTV) ratio.

between two risk factors: borrower illiquidity decreases and leverage increases. We then estimate the risk level (i.e., default probabilities) through the data of traditional contracts and calculate the implied risk level for the new contracts using updated risk factors. This method may also be used to study other contract designs.

Third, we benchmark the new contracts to FRMs and two common ex-post loan modifications: deferred principal only FRMs (DPFRMs) and deferred FRMs (DFRMs) within which borrowers defer all repayments during economic downturns conditional on borrower delinquencies over 60 days. Comparing risk and return for mortgage portfolios over lifetime and age, we find that the new contract designs reduce idiosyncratic risk, systematic risk, and regulatory capital, resulting in an overall increase in return-on-capital (ROC) ratio or a decrease in credit spread.[53]

Efficiency gains may benefit lenders, consumers, or both depending on their balance of power. We find that the ex-ante contracts help reduce mean PD, systematic risk, and regulatory capital. AFRMs can significantly lower the mean PD by 13 percent and systematic risk by 19 percent. These reductions lead to a drop in regulatory capital by almost 10 percent. In terms of economic impact, using AFRMs allows lenders to achieve a better ROC ratio of approximately 10 percent higher than FRMs. Alternatively, borrowers may benefit from a 10 percent drop in funding costs, equivalent to 17 basis points in credit spreads. We observe a similar but much weaker impact under IFRMs. In summary, we find that adopting either AFRMs or IFRMs will boost competitiveness in the mortgage markets and perhaps bolster the national economy.

The remainder of this chapter is organized as follows: Section 3.2 reviews the contract designs in the literature; Section 3.3 introduces benchmark contracts and design innovations;

[53] Idiosyncratic risk and systematic risk are constituents in the calculation of economic and regulatory capital and hence the basis of return calculations by lenders. Systematic risk is defined as the level of co-movement of PD in a model that accurately follows observed default rate over time (see e.g., Hilscher & Wilson (2017)). Idiosyncratic risk is defined as the risk that is not attributed to systematic risk. Most contracts analyzed in this paper have lower average probability of default (PD) and peak PD during the Global Financial Crisis. See for example, first chart (top) in Figure 3.11. The link between optimal mortgage contract design and macroeconomic resilience has been theoretically discussed by Campbell et al.(2021), Greenwald et al. (2021), Guren et al. (2021). To date, there is limited empirical evidence.

Section 3.4 describes the research framework in combination with the main empirical results; Section 3.5 reports the robustness test results; and Section 3.6 summarizes findings, policy implications, and future work.

3.2 Literature review

3.2.1 Mortgage contract designs

FRMs and similar ex-post loan contract designs have been studied, while research on ex-ante contracts which optimize loan serviceability is undergoing debate with limited empirical evidence. Table 3.1 provides an overview of this literature.

Table 3.1: Literature review on mortgage contracts

Paper	Contract type	Adjustment	Trigger	Analysis
Piskorski and Tchistyi (2010)	ARM	Flexible repayment	Option by borrower	Theoretical
Piskorski and Tchistyi (2011)	ARM	House price changes the credit limit	House price increase	Theoretical
Eberly and Krishnamurthy (2014)	FRM	Switch from FRM to ARM	Interest rate decrease	Theoretical
Campbell et al. (2021)	ARM	Pay interest only	Recession	Theoretical
Guren et al. (2021)	FRM	Switch from FRM to ARM	Recession	Theoretical
Greenwald et al. (2021)	SAM	Indexation of periodic payments to house prices	Automatic	Theoretical
Amromin et al. (2018)	ARM	Interest-only and Negative-amortization mortgages	Automatic	Empirical
Cocco (2013)	ARM	Lower initial payments	Option by borrower	Empirical
LaCour-Little and Yang (2010)	Alt-A ARM	Interest-only and other deferred amortization	Automatic	Empirical
Fuster and Willen (2017)	Alt-A ARM	Interest rate reductions	Interest rate decrease	Empirical
Agarwal et al. (2023)	FRM	Reduction in interest rate	Option by lender	Empirical
Agarwal et al. (2017)	FRM	Principal reduction	Option by lender	Empirical
Barr et al. (2019)	Income-contingent loan	Repayment depends on current borrower income	Automatic	Empirical

3.2.1.1 Ex-post contracts

Economic downturns generally coincide with interest reductions, which increase borrower liquidity. The most common contracts are hybrid contracts, in which borrowers start with FRMs and can explicitly switch to ARMs when the interest rate significantly falls during a crisis. Eberly and Krishnamurthy (2014) and Guren et al. (2021) propose FRMs with an additional option to refinance or convert ARMs if borrowers face financial difficulties. On the one hand, this contract allows borrowers to take advantage of a lower interest rate during the downturn. On the other hand, as borrowers do not have a general right to refinance, the requirements around bank lending standards and level of personal credit risk are critical at the time of refinancing.

Fuster and Willen (2017) analyze ALT-A (or near-prime) hybrid mortgages and argue that payment reductions due to lower interest rates reduce the delinquency rate by about 55 percent during the economic downturn period of 2008-2011. While this approach might be beneficial for borrowers in helping them keep making the repayments, this design does not directly consider the borrowers' liquidity shock due to unemployment or illness. Campbell et al. (2021) combine ARMs with designated options for borrowers to pay interest only during economic downturns. These designs are comparable to loan (payment) deferments during the COVID-19 pandemic and are not sensitive to borrower circumstances.

The US government launched the Home Affordable Refinance Program (HARP) and Home Affordable Modification Program (HAMP) in 2009 to further relax the liquidity constraint for households during the housing crisis. HARP supports the refinancing of negative equity loans and HAMP provides incentives to lenders to renegotiate mortgage terms with distressed borrowers. Agarwal et al. (2017) and Agarwal et al. (2023) find that these programs lower foreclosure rates and boost the housing market's recovery. However, these programs may require government and taxpayer support. Furthermore, Cordell et al. (2009) suggest that this program may not be suitable for those suffering job loss. Haughwout et al. (2016) document a decline in the second-time default rate and highlight the modification costs. Been et al. (2013) show that modification decisions are based on borrower characteristics such as LTV, FICO, the neighborhood housing price appreciation, and whether borrowers receive foreclosure counseling.

3.2.1.2 Ex-ante contracts

There is a dearth of research in the literature on ex-ante contract designs. Lenders sometimes offer contracts that attract new customers by introducing lower teaser (also known as honeymoon rates) to borrowers in earlier periods of loan lifetimes and compensate these with higher interest rates in later periods. Empirical evidence suggests that these expense shocks increase default risk during economic downturns (Mayer et al., 2009).

Piskorski and Tchistyi (2010) theoretically describe an optimal contract with an adjustable rate and allow borrowers to choose flexible repayments as long as the loan balance is below a specific limit and borrowers promptly report their incomes to lenders. This is an example of negative-amortization mortgages. These contracts may align with borrowers' circumstances as borrowers can make the repayments according to their income levels. Nevertheless, this method may expose lenders to moral hazard risk and additional operational expenses.

As an alternative, Barr et al. (2019) examine the income-contingent loans for a sample of student loans in Australia and England. With this contract, monthly or fortnightly repayments depend on the borrowers' future income with a fixed repayment ratio and hence assure loan serviceability during difficult times. The loan repayment rates are fixed, while the time to maturity may vary with realized post-graduation incomes. This approach reflects the alignment to borrowers' circumstances, but the uncertain repayment schedule may be too risky for some lenders.

Most ex-ante designs are negative-amortization mortgages, such as interest-only loans with balloon payment, and their merits have been debated in the literature. LaCour-Little and Yang (2010) find that these mortgage designs are more likely to be selected by borrowers with greater risk profiles. Cocco (2013) adds to this, stating that these mortgages benefit young borrowers with limited financial wealth. They can also take advantage of interest tax deductibility and fewer transaction costs. In contrast, Amromin et al. (2018) find that interest-only and negative-amortization mortgages are more common among households with high-income levels and good credit scores. Despite these risk-mitigating effects, they observe that delinquency rates are twice as high as for FRMs.

Instead of indexing repayments to borrowers' income, Greenwald et al. (2021) mitigate leverage shocks through shared appreciation mortgages, suggesting the indexation of periodic payments to house prices. Lenders and borrowers share the house price risk, in which lenders provide borrower payment reductions when house prices fall, and payment increases when house prices rise. Indexing mortgage payments to local house prices may reduce financial fragility and improve risk-sharing. We do not link cash flows to house prices as Basel capital rules require complete (100 percent) capitalizations for equity exposures. Aragon et al. (2010) argue that tax rules make developing this contract in the US market difficult.

3.2.1.3 Guiding principles

A large number of mortgage contracts exist. Some examples are interest-only, balloon, adjustable-rate mortgages, and hybrid loans, but they tend to be limited in volume. As most mortgage loans are based on FRMs, our new contracts will be developed on this basis. We will investigate enhancing liquidity options for FRMs in a way that reduces overall risk while maintaining a level of return that is comparable to current mainstream mortgage contracts. We require the following features as they have the potential to be sought after by consumers and provided by lenders in large volumes:

- 30-year maturity: primary originations are generally for 31- to 35-year-old borrowers (Halket & Vasudev, 2014). A 30-year maturity is suitable to ensure repayment before retirement.
- Fixed rate: our mortgage contracts have a fixed interest rate, but repayments vary as we apply growing annuities. There are no interest rate risks for consumers.
- Ex-ante deterministic and borrower-specific minimum scheduled payments and scheduled loan balances. Consumers can better align payments with their financial plans and net incomes.
- Loan profiles are aligned with standard banking practices, in particular, taxation laws

and the Basel Committee on Banking Supervision regulations.

We do not consider contracts that are not aligned with these principles (e.g., loans indexed to interest rates, interest-only, or balloon loans).

3.2.2 Mortgage default risk literature

We benchmark our novel contracts to traditional FRMs and the ex post contracts using a model for probability of default (PD) in a counterfactual analysis.[54] The literature has identified two key factors of default risk, which are illiquidity and leverage (i.e., DTM). Our new contracts impact both risk factors.

Different proxies for illiquidity have been analyzed. Elul et al. (2010) use utilization ratio of credit card lines, Campbell and Cocco (2015)the loan-to-income ratio, Schelkle (2018) the debt-to-income (DTI) ratio, and Gerardi et al. (2018) the changes in employment status. There is a stronger consensus on the use of leverage proxy. Most studies use the ratio of the outstanding loan balance to the house value (LTV). This ratio relates to fluctuations in house value and loan amortization.

Other common factors include specific information on the borrower, loan, collateral, and macroeconomy. The common findings from previous studies show that higher FICO scores, loans with multiple borrowers, and smaller loan amounts have a lower default risk. Other factors that explain default risk are the property type, owner's occupancy status, and origination channel. The judicial system is also one of the crucial factors for mortgage risk. Ghent and Kudlyak (2011) show that borrowers in non-recourse states are more sensitive to negative equity and more likely to default than in recourse states.[55]

The previous literature indicates that the relation between borrower age and PD is

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[54] We provide the step-to-step details in Section 3.4.

[55] Since we emphasize the role of liquidity, we only analyze loans originated in recourse states. However, we provide the robustness test with the full sample including mortgages from both recourse and non-recourse states.

nonlinear, in that the PD of middle-aged borrowers are higher than those of younger and older borrowers (Debbaut et al., 2016). Djeundje and Crook (2019) include splines and polynomial terms in PD models to address this nonlinearity.

For macroeconomic variables, Amromin and Paulson (2009) investigate the impact of real estate prices. Unemployment rate and GDP growth are also macroeconomic factors that have been found to be significant (Elul et al., 2010; Schelkle, 2018). Gerardi et al. (2018) examine the effects of unemployment (next to disability and divorce) using survey data. Goodstein et al. (2017) and Gupta (2019) scrutinize contagion effects for mortgages and Azizpour et al. (2018) for corporate loans.

In terms of methodologies, most papers employ generalized linear models with probit or logit link functions (i.e., probit or logistic regressions) to estimate the probability of default (see, Elul et al., 2010; Gathergood, 2009; Kelly & O'Toole, 2018; Linn & Lyons, 2020). These regressions consider the default of mortgages and ignore competing risks such as payoff. To control competing risk bias, the mortgage literature employs multinomial logit regressions (see, Heinen et al., 2021; Luong & Scheule, 2022; Pennington-Cross & Chomsisengphet, 2007).[56] In our study, we follow this approach and test other methods, including the traditional logit regression with and without polynomial terms in the robustness tests.

3.3 Benchmark mortgage contracts and contract innovations

Our proposed contract designs have fixed interest rates and maturities, but do not require constant annuity payments as we adjust principal repayments over time to optimize DTI and LTV based on borrower features. We benchmark these contracts to current industry practices.

The Consumer Expenditure Survey from 2004 to 2014 conducted by the Bureau of Labor Statistics shows that approximately 86 percent of mortgages are FRMs. The reason for the

[56] We have also run a competing risk hazard model following the extended Cox proportional hazard model by (Fine & Gray, 1999) with consistent results.

popularity of FRMs are predetermined repayment schedules that limit borrower uncertainties. Lenders have interest risk due to the origination of long-dated fixed-rate mortgages funded by short-dated (i.e., more frequently repriced) deposits. These risks are well-managed as lenders transfer these risks via interest rate swaps to other market participants.

It is current industry practice to modify mortgage liquidity or leverage ex-post if borrowers have difficulties making repayments. The implementations of the HARP and HAMP programs in 2009 following the severe impacts of the GFC are examples. During the COVID-19 pandemic, many countries implemented deferral plans allowing borrowers in hardship to suspend and defer loan payments. Deloitte (2020) reports the impact of COVID-19 on global residential mortgage markets and describes these plans for the US, UK, Australia, Canada, Italy, and China. These plans relieve financial stress for borrowers in the short term. However, borrowers face higher debt levels following the deferral periods as they are required to repay missed payments. We have included two downturn-adjusted FRMs, which allow borrowers to defer principal payments or all payments as another benchmark. In the following, we detail the benchmark FRMs and ex-post contracts and ex-ante contract innovations.

3.3.1 Benchmark fixed-rate mortgages (FRMs)

FRMs are fully amortized mortgages with fixed interest rates. Borrowers make annuity payments consisting of interest payments and principal repayments. The interest proportions decrease, and the principal proportions increase over time as the outstanding principals reduce. Annuities and 30-year maturities are chosen to reduce the illiquidity constraints of borrowers by aligning scheduled payments to the free cash flows (i.e., the difference between incoming and non-discretionary outgoing cash flows) over the larger part of the work-life of borrowers. The equation for annuity A is:

$$A = \frac{B * i}{1-(1+i)^{-n}} \tag{3.1}$$

A is the annuity, B is the original balance, i is the loan contract rate, and n is the number of periods from origination to maturity. We omit a loan/borrower index for simplicity. The scheduled balance (SB) is the difference between the future value of the original loan balance and the annuities paid:

$$SB_t = B(1+i)^t - \frac{A*[(1+i)^t - 1]}{i} \tag{3.2}$$

3.3.2 Benchmark ex-post contracts

Ex-post contracts initially follow the payment pattern of FRMs, and adjustments are made when borrowers face hardship, particularly during economic downturns. The first is a deferred principal-only fixed-rate mortgages (DPFRMs) contract in line with Campbell et al. (2021). This contract is identical to traditional FRMs during normal periods, and payments switch to interest-only whilst principal repayments are deferred in economic downturns. After the deferral period, borrowers need to pay higher annuities to amortize the loans over 30 years. Loan extensions are not considered as borrowers are limited to the periods prior to retirement.

The annuities A and scheduled balances SB are initially calculated with the same equations (i.e., Eq. (3.1) and (3.2)) used for FRMs. The periodic payments during stress time are calculated based on the loan balance before stress, while the scheduled balances are unchanged for *j* periods. After the stress time, annuities are repriced, and borrowers pay a different annuity following the deferral of principal (ADP) until maturity. The calculation of ADP and the scheduled balance (SBDP) following the deferral of the principal is as follows:

$$ADP = \frac{SB_{d1}*i}{1-(1+i)^{-(n-d2+1)}} \tag{3.3}$$

$$SBDP_t = SB_{d1} * (1+i)^{t-d2+1} - ADP * \left[(1+i)^{t-d2+1} - 1\right]/i \tag{3.4}$$

d_1 is the last observation before the deferral period, and d_2 is the end of the deferral period.

The second is a deferred fixed-rate mortgages (DFRMs) contract where borrowers can defer both interest and principal. This contract is similar to the deferments provided to borrowers during the COVID-19 pandemic. The missed interest payments will be accumulated and added to the loan balances. After the adjustment periods, borrowers need to repay higher annuities for the remaining maturity. The calculation of the scheduled balance during the stress time (SSB) is as follows:

$$\mathrm{SSB}_{\mathrm{d1,d2}} = \mathrm{SB}_{\mathrm{d1}} * (1 + \mathrm{i})^{(\mathrm{d2}-\mathrm{d1})} \tag{3.5}$$

The calculations of the annuity (AD) and post-extension scheduled balance (SBD) following the deferral of all payments are adjusted as follows:

$$\mathrm{AD}_{\mathrm{d1,d2}} = \frac{\mathrm{SSB}_{\mathrm{d1,d2}} * \mathrm{i}}{1-(1+\mathrm{i})^{-(\mathrm{n}-\mathrm{d2}+1)}} \tag{3.6}$$

$$\mathrm{SBD}_{\mathrm{t,d1,d2}} = \mathrm{SSB} * (1 + \mathrm{i})^{\mathrm{t}-\mathrm{d2}+1} - \mathrm{AD}_{\mathrm{d1,d2}} * \left[(1 + \mathrm{i})^{\mathrm{t}-\mathrm{d2}+1} - 1\right]/\mathrm{i} \tag{3.7}$$

Figure 3.2 visualizes the periodic payment and loan balance of ex-post contracts (dashed line) compared to FRMs (solid line) over time. For illustrative purposes, we assume an example loan with an original balance of \$100,000, a fixed interest rate of 5 percent, and a maturity of 30 years. For FRMs, the borrowers pay roughly \$6,442 per annum. The amortization speeds are initially slow but increase toward the end of maturities. We assume that the shock appears in year 12, and the deferment policy starts from year 13 due to the delayed effect on the mortgage market. The payment during the downturn adjustment of DPFRMs is \$3,762, which increases to \$6,842 to repay the principal over the remaining maturity. For DFRMs, the borrowers make no payment during the downturn and pay an annuity of \$7,560 during the post-deferment period.

In the empirical analysis, we apply deferral treatment to those who are delinquent on their loans over 60 days during the economic downturn. Delinquent borrowers receive relief as they only make interest or no payments and are unlikely to default during the crisis. This feature highlights the importance of this contract in reducing default clustering or systematic risk. Due to the deferred payments, default risk shifts from downturn periods to later periods and mitigate the systematic risk during economic downturns.[57]

Regulators have supported the deployment of downturn adjusted FRMs during COVID by considering loan deferrals as performing, i.e., non-delinquent and non-defaulted loans. This is important as delinquencies otherwise trigger higher loan loss provisions that may

[57] The default risk post-deferment does not reduce to zero as we analyze model implied default rate (i.e., even if DTI is zero, the default probabilities for loans are non-zero positive).

disincentivize lenders.

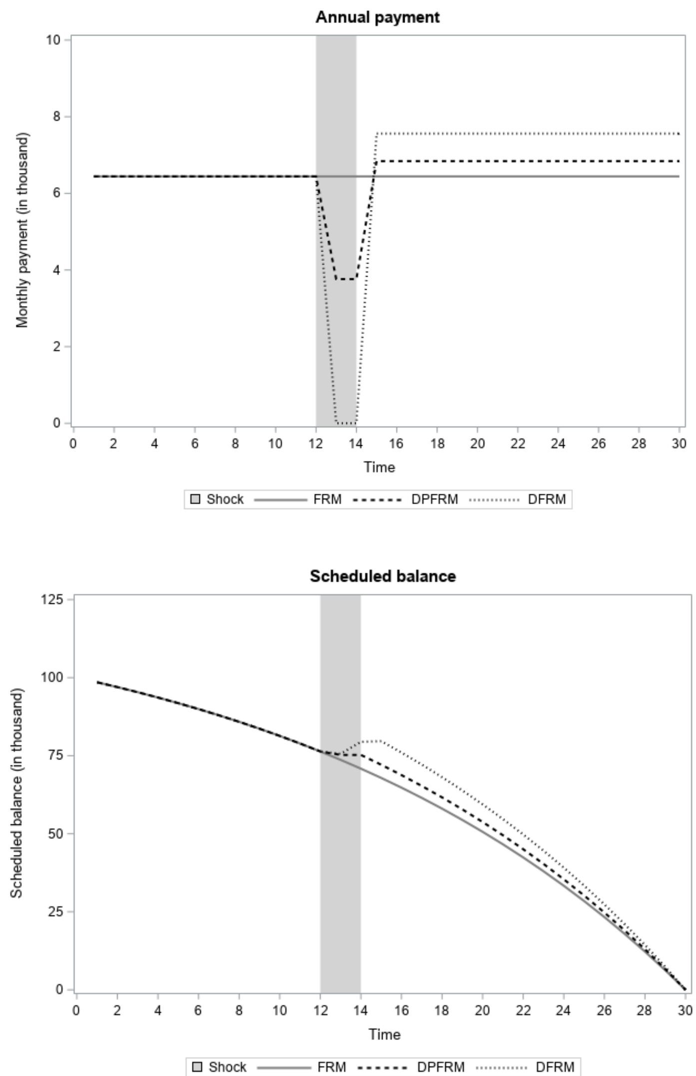

Figure 3.2: Monthly payment and scheduled balance: FRMs vs. ex-post contracts

Note: This figure shows the monthly payments (top) and the scheduled loan balances (bottom) of ex-post contracts compared to FRMs for an example loan. The solid line refers to FRMs, the dashed line refers to DPFRMs, and the dotted line refers to DFRMs. For FRMs, the periodic payment is computed by Eq. (3.1) and the scheduled balance is computed by Eq. (3.2). For DPFRMs after the downturn-adjustment period, the periodic payments are computed by Eq. (3.3) and the scheduled balance is computed by Eq. (3.4). For DFRMs after the downturn-adjustment period, the periodic payments are computed by Eq. (3.6) and the scheduled balance is computed by Eq. (3.7). These calculations are done at monthly frequency. We take the sum of all monthly periodic payments as the annual payment and take the last value of scheduled balance as the annual scheduled balance. The example loan's amount at origination is 100,000, the contract rate is 5 percent, and the time to maturity at loan origination is 30 years. We assume that the shock happens in month 133. The effect of the downturn on the mortgage market tends to be delayed, so the downturn-adjustment period starts a year later at month 145 (year 12) and lasts for two years.

Lenders may offer borrowers the option to extend the loan term or modify the repayment schedule during non-downturn periods using such transitionary arrangements (phasing back interest and principal payments may be included in practice). We do not consider these as the empirical results will be similar, and it would make the thesis too complicated as these contracts are only a benchmark and not the main subject of the thesis which are IFRM and AFRM contracts. This may be an approach to maintaining the same payments during non-downturn periods. This flexibility can provide borrowers with temporary relief by reducing their monthly payment obligations. However, it is important to note that extending the loan term may result in higher overall interest costs for borrowers. Alternatively, lenders can explore the possibility of implementing income-based or age-related repayment plans.

3.3.3 Ex-ante contracts

We introduce two ex-ante personalized contracts: an income-adjusted fixed-rate mortgage and an age-adjusted fixed-rate mortgage. Our novel contracts are created based on FRMs with the incorporation of liquidity enhancement features. Ganong and Noel (2022) find that liquidity is the primary driver of borrower default and consumption decisions. Using administrative and survey data, Low (2021) confirms that liquidity shocks dominate negative equity in triggering nearly all defaults. Therefore, our aim is to personalize the mortgage payments to optimize borrower liquidity, reduce default risk and improve system resilience.

3.3.3.1 Income-adjusted fixed-rate mortgages (IFRMs)

The average annual income growth from 1999 to 2019 at the state level is 2.5 percent per annum (see Table 3.2). FRMs do not account for income growth. Indexing periodic payments to the income growth may better align loan amortizations with borrowers' liquidity. Borrowers will pay less at the beginning and more later as their incomes are likely to grow as time passes. Consequently, borrowers may have less (more) difficulty making payments towards the start (end) of maturities relative to FRMs when risks are high (low).[58]

We derive IFRMs from traditional FRMs by replacing the annuity with growing annuities, i.e., increasing periodic payments at constant growth rates, which are the average annual growth rates at the state level. We acknowledge fair lending practices by using states rather than zip codes, as otherwise, the neighborhood's socioeconomic features may determine the individual borrower's contract features.[59] Nevertheless, IFRMs are personalized as income growth rates are applied to borrowers' incomes. We first calculate the initial payment for IFRMs (AI) from the present value (here B) of a growing annuity:

$$B = \frac{AI_s}{i - g_s}\left(1 - \left(\frac{1+g_s}{1+i}\right)^n\right) \tag{3.8}$$

$$AI_s = \frac{B(i - g_s)}{\left(1 - \left(\frac{1+g_s}{1+i}\right)^n\right)} \tag{3.9}$$

where B is the original loan balance, i is the interest rate, and n is the loan's maturity. g_s is the historical average annual income growth for state s. The initial payment is lower than FRMs' annuities and will be compounded by the state-level growth rates in future periods. We then compute the scheduled payments for IFRMs (SPI) at times t as growing annuities by compounding the first payment annuity for the expected income growth rate from period 2 (t-1>=1 from t=2) following Eq. (3.9):

$$SPI_{st} = AI_s(1 + g_s)^{t-1} \tag{3.10}$$

The scheduled loan balance (SBI) for IFRMs at time t is the difference between the future values of the origination balance and the future values of all repayments paid before t:

$$SBI_t = B(1 + i)^t - \sum_{t=1}^{n} SPI_t(1 + i)^{t-1} \tag{3.11}$$

To illustrate, we re-use the example loan with a loan size of \$100,000 and an interest

[58] In Australia and England, income-contingent student loans exist (see Barr et al., 2019). The differences between IFRMs and this system is that the interest rates and durations are fixed to comply with our guiding principles.

[59] We provide robustness checks for zip code level.

rate of 5 percent and assume an income growth rate of 2.5 percent.[60] The first payment for IFRMs is $4,803, which is lower than traditional FRMs at $6,442. These payments are lower than FRMs during the first 12 years and gradually increase to around $10,000 at the end of maturity. The scheduled balances for traditional FRMs are smaller than for IFRMs.

A more conservative approach in terms of assumed income growth would involve considering scenarios where income growth is below the historic average rate of 2.5 percent. This approach acknowledges the possibility of economic uncertainties and ensures that mortgage contracts are designed to be resilient even in adverse income conditions. We consider such assumptions in our robustness checks. By incorporating lower income growth assumptions into the design of personalized mortgage contracts, lenders can better assess the borrower's ability to make payments and mitigate the risk of default during periods of lower income growth.

3.3.3.2 Age-adjusted fixed-rate mortgages (AFRMs)

FRMs do not account for life cycles. Figure 3.1 shows that the default rate follows a hump shape with age. Most first-time borrowers apply for mortgages in their early thirties, and default risk may peak due to borrower events leading to loss of income (e.g., by unemployment, disability, or divorce) or expense increases.[61] The reasons why borrowers' default risk may reduce after year nine are (1) their financial stress is likely relieved due to a more stable income and a reduction in expenses and (2) they have built a considerable equity in their homes making them unlikely to default. As an alternative to IFRMs, we consider age-adjusted fixed-rate mortgages (AFRMs) contracts where payments are aligned by the age risk pattern. AFRMs differ from IFRMs as the life cycles are non-linear, as Figure 3.1 suggests, and do not correspond to the linear pattern of expected income growth.

The construction of AFRMs is empirically based on the effects of loan age and borrower-specific DTI. We describe the determination of the growth rates for the repayments in the

[60] This is the average income growth at the state level over the sample.

[61] See Gerardi et al. (2018); Halket and Vasudev (2014); Luong and Scheule (2022)

empirical part.[62] These growth rates are small if borrower liquidity risk is high and vice versa. Further, AFRM repayments inversely relate to the hump-shape age risk pattern, meaning that repayments steadily decrease before the peak (negative growth rate) and increase after the peak of default risk by loan age (positive growth rate). To maintain predictability in periodic payments, we use formulas for growing annuities with two growth periods and rates: a negative growth rate k_1 until the peak risk period (p) and a positive growth rate k_2 after that (i.e., from p+1 to n). The first repayment for AFRMs (AA) is:

$$B = AA * PV_1 + \frac{AA*PV_2(1+k_1)^{p-1}(1+k_2)}{(1+i)^p} \tag{3.12}$$

$$AA = \frac{B(1+i)^p}{PV_1(1+i)^p+PV_2(1+k_1)^{p-1}(1+k_2)} \tag{3.13}$$

with peak risk period p, the present values for the first growth rate regime for a \$1 annuity $PV1 = \frac{1}{i-k1} - \frac{1}{i-k1}\left(\frac{1+k1}{1+i}\right)^p$ and the present values for the second growth rate regime in period m for a \$1 annuity $PV2 = \frac{1}{i-k2} - \frac{1}{i-k2}\left(\frac{1+k2}{1+i}\right)^{(n-p)}$. The scheduled payment is as follows:

$$SPA_t = \begin{cases} AA(1+k_1)^{t-1} & \text{if } t \leq p \\ AA(1+k_1)^{p-1}(1+k_2)^{t-p} & \text{if } t > p \end{cases} \tag{3.14}$$

Up to the peak period, the repayment is reduced with a negative growth of k_1 from the first repayment. At the peak time p, the repayment is $AA(1+k_1)^{p-1}$ which is used as the starting point of the second regime with the positive growth rate of k_2 until the end of maturity.

We generalize the scheduled payment for any number of growing annuities in Appendix 3.B. We finally calculate the scheduled balance SBA over time as the future value of the origination balance less the future value of all prior annuity payments:

$$SBA_t = B(1+i)^t - \sum_{t=1}^{n} SPA_t(1+i)^{t-1} \tag{3.15}$$

To illustrate this contract, we utilize the same example loan with an original balance of

[62] See Section 3.4.

$100,000, an interest rate of 5 percent, and a maturity of 30 years. We observe in Figure 3.1 the peak default rate in year 9. Assuming k_1 is -14 percent and k_2 is 10 percent. The initial annual payment is $8,483, gradually decreasing to $2,720 at peak time and then steadily increasing to nearly $20,000 for the last payment. As a result, the scheduled balances for AFRMs are initially higher than FRMs and converge to zero at maturity.

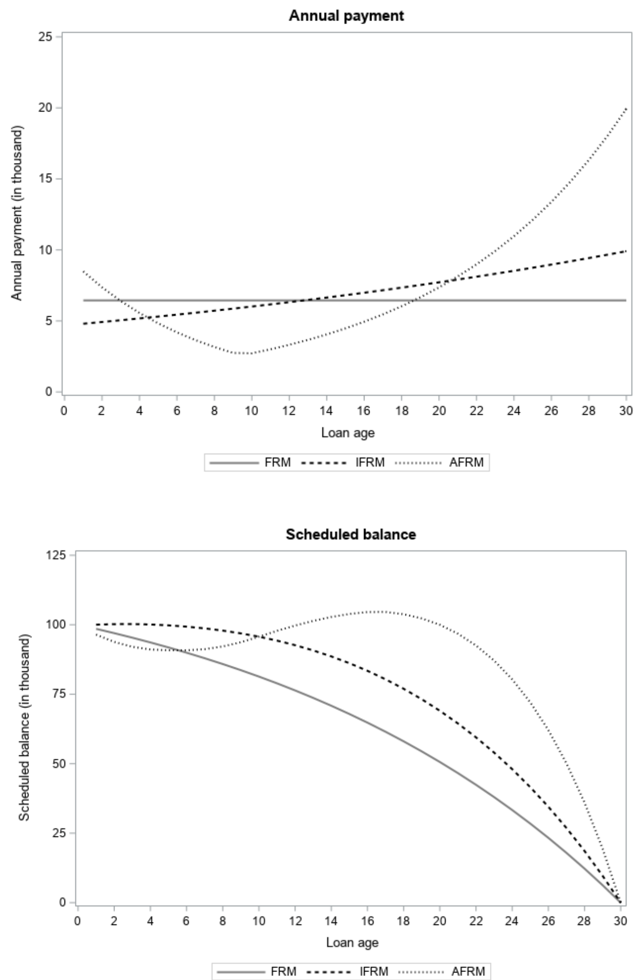

Figure 3.3: Monthly payment and scheduled balance: FRMs vs. ex-ante contracts

Note: This figure shows the monthly payments (top) and the scheduled loan balances (below) of ex-ante contracts and a benchmark fixed-rate mortgage contract for an example loan. The solid line refers to FRMs, the dashed line refers to IFRMs, and the dotted line refers to AFRMs. For FRMs, the periodic payment is computed by Eq. (3.1) and the scheduled balance is computed by Eq. (3.2). For IFRMs, the periodic payments are computed by Eq. (3.10) and the scheduled balance is computed by Eq. (3.11). For AFRMs, the periodic payments are computed by Eq. (3.14) and the scheduled balance is computed by Eq. (3.15). These calculations are done at monthly frequency. We take the sum of all monthly periodic payments as the annual payment and take the last value of scheduled balance as the annual scheduled balance. The example loan's amount at origination is 100,000, the contract rate is 5 percent, and the time to maturity at loan origination is 30 years. We use the average income growth g of 2.5 percent (p.a) to calculate the periodic payment and scheduled balance for IFRMs. We use the average k_1 and k_2 of 15 percent and 10 percent (p.a) to calculate the periodic payment and scheduled balance for AFRMs.

Figure 3.3 provides charts for the periodic payment and scheduled balance of ex-ante contracts compared to FRMs over time. The dashed lines are for IFRMs, and the dotted lines are for AFRMs.

The proposed personalized mortgage contracts take historical borrower income and risk into account. Future wage growth and risk over age or their expected levels may be different. The presented contracts may accommodate predicted levels. Ultimately, such models may have a limited impact as models including Vector Auto Regressions converge to historic averages after a few years. Note that predictions would have to cover the lifetime of mortgages, i.e., 30 years. Further, there may be a concern about the distance between the borrower's expected wage growth and their local area, but this helps to maintain fair lending practices. While models may be too general and not always align with local area trends, I have provided the robustness check where the income growth is calculated at the zip code level and the results remain consistent.

The ex-ante contracts aim to reduce the probability of default and enhance financial system resilience. The goal is to provide borrowers with more flexibility in managing their mortgage payments and reduce the likelihood of default triggered by liquidity shocks. The intention is to create a win-win situation for both borrowers and lenders by reducing default risk and increasing competitiveness in the mortgage market. However, the contracts may also increase the outstanding principal values and reduce equity values. It is unclear whether income or age adjusted contracts provide incentive misalignments as borrowers may choose to use extra funds to increase their investment into housing or risky alternatives. The consequences may be higher house prices or greater leverage and hence risk to households. These unintended consequences may ultimately be an empirical question.

Whilst we cannot measure such effects with historical data, lenders may consider phasing in these contracts for selected projects and transitionary arrangements. In the robustness checks we analyze alternative contract designs including a hybrid FRM (HFRM) contract that does not lower the mortgage payments prior to the peak risk year and increases payments as risk reduces thereafter.

3.4 Empirical analysis

We analyze mortgage contracts that have not been implemented to date, and thus credit outcomes cannot be observed empirically. Hence, we proceed in five steps. First, we observe features and credit outcomes for FRMs in a panel format. We analyze large portfolios of US mortgages originated by multiple lenders. Second, we fit a probability of default model for FRMs. Third, we compute updated features for our new contract designs and ex-post modifications. The model includes time-varying macroeconomic factors and the implied default probabilities approximate realized default rates effectively. This assumption is common in the literature (e.g., Hilscher & Wilson, 2017). Fourth, using the new contract design, we predict the model-implied default probabilities for the revised features. In a final step, we compare the mean PD for ex-post and ex-ante contracts and derivatives thereof, including systematic risk level (i.e., the difference between peak PD and mean PD), regulatory capital, and the return on regulatory capital (ROC). The calculation of regulatory capital assumes that this lender is a bank regulated by the Basel regulations. Non-bank lenders are not subject to these rules but may apply similar risk measurement concepts. Figure 3.4 visualizes the process of the empirical counterfactual analysis.

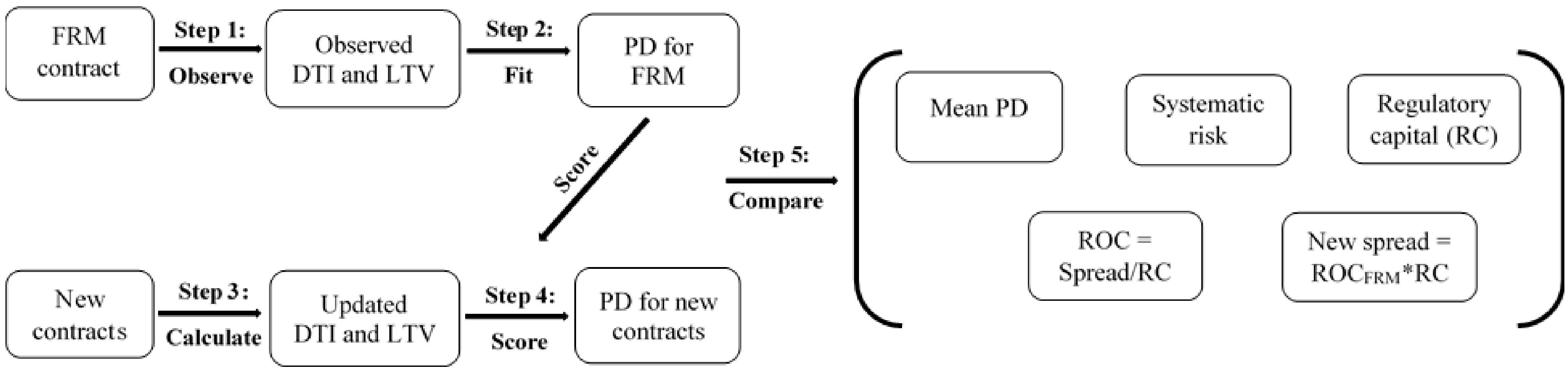

Figure 3.4: Research framework

Note: This figure shows the process of our empirical counterfactual analysis, which is necessary as the borrower performances cannot be empirically observed.

3.4.1 Observed data (Step 1)

3.4.1.1 Mortgage data and filter rules

We collect data on single-family mortgage loans from Freddie Mac.[63] The database covers mortgages originated by banks and non-bank lenders, including information collected at the origination period and monthly loan performances.[64] Data is collected in monthly intervals from January 1999 to December 2019. We remove all observations with missing values in loan features.[65] The current sample contains more than one billion loan-month observations.

From the original data, we focus on 30-year purchase FRMs from recourse states.[66] Recourse loans are sensitive to leverage (LTV) as the house asset is security as well as illiquidity (DTI) as general borrower assets are also secondary securities. According to Ghent and Kudlyak (2011), borrowers in non-recourse states are more susceptible to walk away from their house loans when the house price drops. Focusing on recourse borrowers highlights the effect of illiquidity on default probability. Recourse borrowing is also the dominant system internationally. We aggregate data to annual frequency and obtain approximately 7 million loans and 33 million annual observations.

3.4.1.2 Income data and other macroeconomic data

The income data is collected from the IRS website[67] and covers 1999 to 2019 at state

[63] http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.page

[64] Roughly 87 percent are standard fully amortizing FRMs with full documentation. The remaining are non-standard loans, including FRMs without full documentation, adjusted-rate mortgages, and other non-amortizing loans. Federal Deposit Insurance Corporation (2019) states that banks sold approximately half, while nonbanks sold more than 97 percent of their 1-4 family originations.

[65] These include FICO, original DTI, original LTV, occupancy status, origination channel, property type, and number of borrowers.

[66] According to state law, non-recourse states include Alaska (AK), Arizona (AZ), California (CA), Connecticut (CT), Idaho (ID), Minnesota (MN), North Carolina (NC), North Dakota (ND), Oregon (OR), Texas (TX), Utah (UT), and Washington (WA). This classification is based on one of the largest mortgage lenders in the US, Quicken Loans (https://www.quickenloans.com/learn/the-difference-between-recourse-and-nonrecourse-loans).

[67] Income by state: https://www.irs.gov/statistics/soi-tax-stats-historic-table-2

and zip code levels. The IRS does not report income at zip code levels in 1999, 2000, and 2003. The data for the missing years is averaged based on the prior and following years. For example, the income data for 1999 is based on an equal split of the growth between 1998 and 2001. We calculate the geometric average growth of the state level's income to construct IFRMs and the annual zip code level's income growth to update the denomination of the DTI ratio.

For other macroeconomic variables, we collect the monthly HPIs at a three-digit zip code level from the FHFA website[68] to estimate the current house value and calculate the current LTVs. We also collect unemployment rate, GDP growth, and national HPI data at an annual frequency from the Federal Reserve Economic Data collection of the Federal Reserve Bank of St. Louis. For contagion, we calculate the average default rate by zip code-year and merge it into the mortgage data.

3.4.1.3 Payment growth rates for AFRMs

The payment growth rates for AFRMs are empirically estimated from the observed mortgage data. Assuming that default risk is driven by liquidity and loan age, we estimate a simple PD model with original DTI, loan age, and its spline at year 9. The effects of other factors are captured in the intercept. To ensure impact scalability between the original DTI and loan age, we run the MNL model with annual observations. We calculate the loan age and DTI effects at each period for every loan using these parameters. The DTI effect is the product of the original DTI and its coefficient, while the loan age effect is the weighted parameter sum of the product of loan age and its spline term.

$$\mathrm{DTI\_effect}_{it} = \beta_{DTI}\mathrm{DTI}_{i\tau} \tag{3.16}$$

$$\mathrm{Age\_effect}_{it} = \beta_{age}\mathrm{Age}_{it} + \beta_{age9}\mathrm{Age9}_{it} \tag{3.17}$$

Income by zip code: https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi

[68] https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

We obtain a constant effect of original DTI throughout the loan maturity and a hump-shape effect of loan age which the peak records at year 9. We further calculate the average loan age effect, which shows the expected risk level from loan age and the difference between the average and time-point loan age effect.

$$\text{Avg\_age\_effect}_i = \frac{\sum_{t=1}^{n} \text{Age\_eff}_{\text{it}}}{n} \tag{3.18}$$

$$\text{Diff\_age\_effect}_{\text{it}} = \text{Avg\_age\_effect}_{\text{i}} - \text{Age\_effect}_{\text{it}} \tag{3.19}$$

Figure 3.5 shows the average loan age effect, the hump-shaped loan age effect, and their difference.

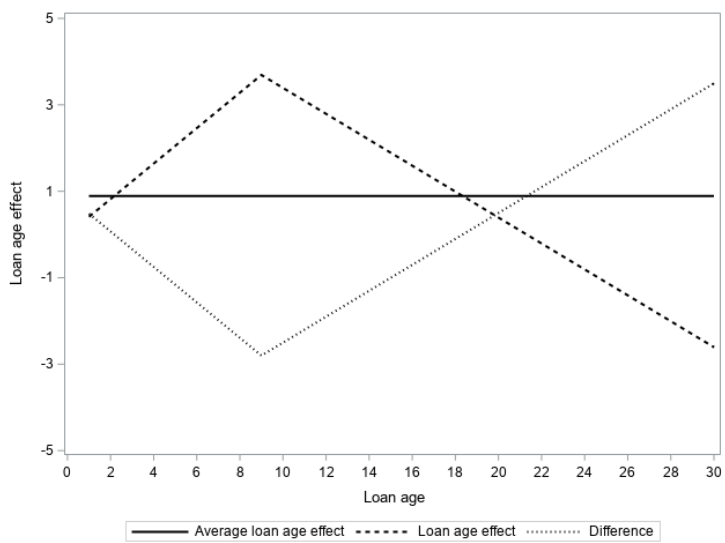

Figure 3.5: Spline age effect over loan age

Note: This figure shows how the effect of loan age (as a spline function) is used to construct the age growth for AFRMs. The hump-shape loan age effect (dashed line) is computed by Eq. (3.17) using the parameter set from a multinomial logit regression using original DTI, loan age, and the spline at year 9. The solid line shows the average loan age effect over time, which is computed by Eq. (3.18). The dotted line shows the difference between the average effect and the loan age effect, which is computed by Eq. (3.19). We incorporate this effect difference into the original DTI effect to adjust the borrower's liquidity. As the original DTI effect is constant over time, the adjusted DTI effect will follow the reversed hump shape according to the difference in loan age effect. Assuming that the borrower's income is stable, cashflows/payments of AFRMs will also reflect the reversed hump-shape pattern.

We observe loan ages up to 21 years and predict up to 30 years via extrapolation to cover the entire loan duration. We combine the difference in loan age with the original DTI effect to get the new DTI effect. Dividing this combination by the DTI coefficient, we obtain the new

DTI.

$$\text{New\_DTI}_{it} = \frac{\beta_{DTI}\text{DTI}_{i\tau} + \text{Diff\_age\_effect}_{it}}{\beta_{DTI}} \tag{3.20}$$

The disparity between the original DTI and the new DTI implies the impact of loan age as the original DTI's effect is constant. We continue calculating the cumulative growth over time as the ratio between the new DTI and the original DTI. This exhibits an inverted-hump shape, meaning payments decrease from the origination to the peak time and increase after that. We take the difference in the cumulative growths between two consecutive periods as the measurement for the annual growth rates of AFRMs. These growth rates are constantly negative from the origination to the peak and positive during the after-peak period. The age-related growth rate varies across the original DTI, in which a lower (higher) original DTI leads to a higher (lower) growth.[69]

$$\text{Age\_gwth}_{it} = \frac{\text{New\_DTI}_{it}}{\text{New\_DTI}_{i\tau}} - \frac{\text{New\_DTI}_{it-1}}{\text{New\_DTI}_{i\tau}} \tag{3.21}$$

$$k_{1i} = \text{Age\_gwth}_{t=1} = \text{Age\_gwth}_{t=2} = \cdots = \text{Age\_gwth}_{t=p} \tag{3.22}$$

$$k_{2i} = \text{Age\_gwth}_{t=p+1} = \text{Age\_gwth}_{t=p+2} = \cdots = \text{Age\_gwth}_{t=n} \tag{3.23}$$

3.4.1.4 Descriptive statistics

We observe roughly 113,000 default events and over 4.7 million payoff events in 33 million annual observations, resulting in an annual default rate and payoff rate of 0.34 percent and 14.3 percent. The high annual payoff rate potentially results in an unbalanced panel and may impact the age-related hump shape of the default rate, which is the foundation of AFRMs. Figure 3.6 shows the relationship between the number of observations (gray bars) and default rate (solid line) over loan age and time with a 99% confidence interval, which widens somewhat for older loans reflecting lower observation counts over loan age. The number of observations

[69] Lower-DTI loans are less risky, hence more risk-tolerance with a higher growth adjustment.

for loans older than 18 years old is very limited; we decide to drop observations after this point.[70]

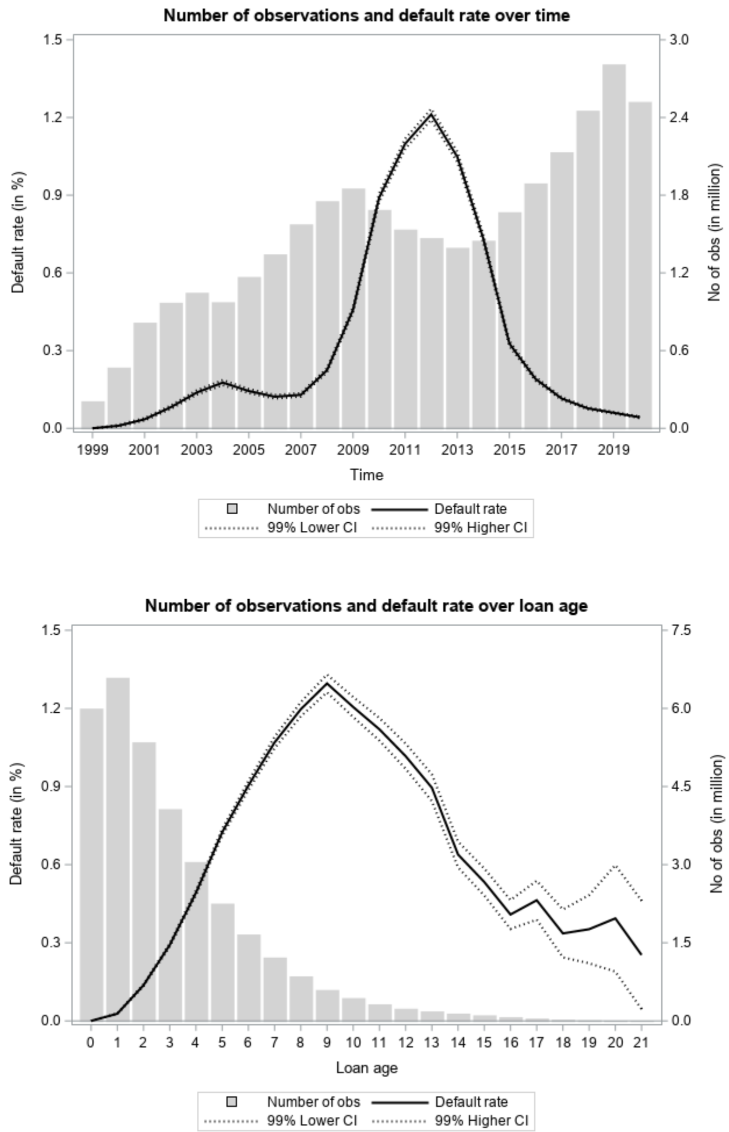

Figure 3.6: Number of observations and default rate

Note: This figure shows the number of observations and default rate over loan age (top) and over time (bottom). The bar chart shows the variations in the number of observations, and the line chart shows the variations in the default rate. Two dashed lines show the 99% lower and higher confidence interval (CI).

[70] This drop removes around 19,000 annual observations.

Table 3.2 presents the descriptive statistics of our data features. We examine the data for all observations and the default and payoff subsamples explain the relation between the default or payoff indicators and explanatory variables.

Table 3.2: Descriptive statistics

Note: This table describes the data from the pooled sample between 1999 and 2019 and for sub-samples of default and payoff loans. The T-test columns examine whether the mean values of each variable related to default or payoff loans are significantly different from the remaining loans. The variable definition is provided in Appendix 3.A.

	Pooled sample		**Default**			**Payoff**		
	Mean	**Std Dev**	**Mean**	**Std Dev**	**T-stat**	**Mean**	**Std Dev**	**T-stat**
Indicator								
Default	0.341	5.829	1.000	0.000		0.000	0.000	
Payoff	14.299	35.006	0.000	0.000		1.000	0.000	
Borrower characteristics								
DTI	30.676	11.101	36.229	12.019	-168.55	31.332	10.670	-139.30
LTV	72.204	21.297	105.875	71.768	-533.85	70.671	20.390	168.66
FICO	739.962	50.954	697.345	56.392	282.03	739.809	50.463	6.64
Loan characteristics								
Orig_Loansize	11.942	0.586	11.826	0.589	66.34	11.995	0.570	-213.06
Mgt insurance	35.869	47.962	57.010	49.506	-148.62	34.748	47.617	55.19
Investment	5.892	23.548	7.800	26.817	-27.31	4.813	21.404	107.72
Prepmt penalty	0.057	2.383	0.105	3.242	-6.78	0.054	2.314	3.17
Multi_borr	51.212	49.985	34.724	47.610	111.15	55.507	49.696	-202.29
TPO	48.806	49.986	58.091	49.341	-62.60	49.445	49.997	-30.12
NotSF	32.364	46.786	33.166	47.081	-5.72	32.368	46.788	-0.34
Interest_rate	5.394	1.220	6.426	0.804	-284.99	5.722	1.267	-634.66
MSA	85.545	35.164	80.376	39.715	49.52	85.265	35.446	18.71
Age	3.089	3.064	6.168	2.932	-336.44	3.844	2.837	-576.85
Macro variables								
HPI_{-1}	525.946	70.501	498.541	43.388	130.93	520.476	77.212	182.96
GDP_Growth_{-1}	4.048	1.820	3.133	2.124	169.46	3.741	1.821	398.13
$Contagion_{-1}$	0.400	0.681	1.478	1.559	-535.72	0.408	0.711	-29.15
Growth factors								
g_s	2.488	0.290	2.429	0.288	67.79	2.489	0.295	-10.70
k_1	-14.938	2.382	-14.027	2.317	-128.79	-14.942	2.388	4.69
k_2	10.924	1.742	10.258	1.695	128.79	10.927	1.746	-4.69
No of obs.	**33,178,421**		**113,176**			**4,746,250**		

Default risk increases for higher DTI, higher LTV, and lower FICO. Loans with mortgage insurance, investment purpose, prepayment penalty, single borrower, third-party originator, and non-single-family homes have higher default risk. Default mortgages also have a higher interest rate and tend to be in rural areas. Regarding macroeconomic variables, default risk increases for lower HPI, lower GDP growth, and higher contagion.

Payoff risk is negatively related to default risk. Payoff loans have lower DTI, lower LTV, and higher FICO than default loans. According to the T-test results, payoff risk significantly increases for bigger loan balances, residency property, and multiple borrowers. The interest rate for payoff loans is almost 1 percent lower than default loans. Payoff risk increases for higher HPI, higher GDP growth, and lower contagion effect than default loans.

We also report the statistics of growth factors for the ex-ante contracts in this table. The state level's income growth is averaged at 2.5 percent per annum. The age growth factors for scheduled payments k_1 and k_2 are estimated at 14.9 percent and 10.9 percent per annum. All growth rates exhibit cross-sectional variation as the standard deviation is positive implying different mortgage repayments and hence balances over the lifetimes of loans.

3.4.2 Modelling probabilities of default for FRMs (Step 2)

We observe a loan outcome of default, payoff, or performance every period. We define a default as foreclosures through a short sale, charge-offs, and real-estate-owned dispositions by banks. The status of loan i at time *t* is indicated as:

$$\mathrm{S_{it}} = \begin{cases} 1 \text{ if default} \\ 2 \text{ if payoff} \\ 0 \text{ if performing} \end{cases} \tag{3.24}$$

We use the multinomial logit (MNL) regression to predict the probability of default for loans using information obtained at the origination time and time-varying covariates. Model parameters can be estimated by maximizing the log-likelihood:

$$\mathrm{LL} = \sum_{\mathrm{i=1}}^{\mathrm{I}} \sum_{\mathrm{t=1}}^{\mathrm{T}} \ln \mathrm{P}(\mathrm{S_{it}} = \mathrm{s}) = \sum_{\mathrm{i=1}}^{\mathrm{I}} \sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{F}(\mathrm{LP}(\mathrm{S_{it}} = \mathrm{s})) \tag{3.25}$$

$F(\mathrm{LP}(\mathrm{S_{it}} = \mathrm{s}))$ is a link function, and $\mathrm{LP}(\mathrm{S_{it}} = \mathrm{s})$ describes the linear predictor, i.e., the parameter-weighted sum of risk factors for outcome s.[71]

First, we include the critical DTM factors: DTI as the proxy for illiquidity and LTV as the proxy for leverage (and negative equity in severe cases). DTI is the ratio of periodic payment and total income. We calculate the average growth rate using the most granular income data obtained at the three-digit zip code level. The borrower's current income is the product of cumulative income growth and original income level. Most studies in this field have utilized either original DTI or unemployment rate as liquidity proxies. LTV is the ratio of the scheduled loan balance to the current house value. We merge the HPI data at the three-digit zip code level with mortgage data, calculate the cumulative HPI growth rate between the current and origination periods, and then estimate the current house values.

Second, we include a wide range of control variables representing borrower and loan characteristics such as FICO scores, original loan sizes, various dummy variables controlling for mortgage insurance, occupancy status, prepayment penalty, number of borrowers, third-party origination channels, underlying property type, and MSA location. We also add the current mortgage rate into our model as this variable may include borrowers' risk levels that are unobserved by other features such as lender soft information.

In addition, we include the loan age as it exhibits the proximities of the loans to maturity. We assume that loan age is a proxy for borrowers' age as we are unable to observe this in the data set. The loan age and its splines are employed to accommodate this nonlinear pattern shown in Figure 3.1. The spline expansions are created by using a truncated power function basis with a degree of unity $T(.)$. In specific, the splines receive values of 0 if the loan age is smaller than the knot and the difference between age and the knots θ_j (threshold, here we assume the age with the highest risk, i.e., year 9) if the age is greater than the threshold. To achieve an ideal fit of the model, we include the knots at year 5, year 7, year 9, year 11, and year 13.

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[71] The probability of payoff may be derived using a second threshold.

$$T(x_{ijt}) = \begin{cases} x_{ijt} - \theta_j \text{ if } x_{ijt} > \theta_j \\ 0 \qquad\quad \text{ if } x_{ijt} \leq \theta_j \end{cases} \tag{3.26}$$

Banks may not have histories spanning over the complete loan lifetimes of generally 30 years. The spline approach with age splines is particularly suited to extrapolate the PD by loan age as it is not limited to the loan ages observed in the estimation sample. Finally, we incorporate the GDP growth, HPI growth, and contagion as macroeconomic factors into the model to control systematic effects.

Our MNL model is given as follows:

$$LP(S_{it} = s) = \alpha_s + \beta_s X1_{it-1} + \gamma_s X2_{i\tau} + \theta_s X3_{t-1} \tag{3.27}$$

where t indicates the current period, τ indicates the origination period, and the subscript "-1" indicates the information available before the end of corresponding period t, i.e., lagged by one period relative to the outcome (default, payoff, or performing) observation. S_{it} is the indicator of performing (0), default (1), and payoff (2). X1 represents variables changing by loan and time; X2 represents variables constant over time and obtains at origination time; X3 represents variables changing by time only.[72] We include dummy variables for mortgage origination years, and the standard errors are clustered by state level. We estimate the default probability (PD) and payoff probability (PP) using the MNL model as follows:

$$PD_{it} = \widehat{P}(S_{it} = 1) = \frac{\exp(\widehat{LP}_{it,1})}{1+\exp(\widehat{LP}_{it,1})+\exp(\widehat{LP}_{it,2})} \tag{3.28}$$

$$PP_{it} = \widehat{P}(S_{it} = 2) = \frac{\exp(\widehat{LP}_{it,2})}{1+\exp(\widehat{LP}_{it,1})+\exp(\widehat{LP}_{it,2})} \tag{3.29}$$

Table 3.3 shows that most coefficients are statistically significant. For the two main drivers of mortgage defaults, we find that the coefficients on DTI and LTV are positive, with DTI having a coefficient of 1.782 and LTV at 0.319. This finding is consistent with the DTM,

[72] X1 includes DTI, LTV, loan age and its splines. X2 includes orig_loansize, mgt insurance, investment, ppmt_penalty, multi_borr, TPO, notsf, interest_rate, and MSA. X3 includes HPI, GDP_growth, and contagion. The variable description is provided in Appendix 3.A.

where illiquidity (higher DTI) and leverage (higher LTV) imply a higher default risk.

The parameter of DTI is greater than the one for LTV for comparable value ranges. This indicates that liquidity may play a greater role in driving mortgage default. This is expected as we only include mortgages originated in states where borrowers face both negative equity and illiquidity as lenders have recourse to the house and general assets of the borrower. To examine whether DTI or LTV is more important to explain PD, we calculate PD elasticities for 1 percent of DTI and LTV of 1.33 percent and 0.58 percent. This finding reinforces the argument that illiquidity triggers play a more significant role in driving default risk than leverage and negative equity in recourse states.

Regarding time-discrete variables, we find that FICO, prepayment penalty, multiple borrowers, and MSA negatively relate to default. Original loan size, mortgage insurance, investment property, third-party originator, non-single-family property, and interest rate positively relate to default. These findings are expected and explainable. The coefficient of loan age is positive, and those of the splines are changing signs to capture the nonlinear effect of loan age on default risk.

Lastly, the effect of GDP growth and HPI on PD are negative, while contagion has a positive coefficient. Higher GDP growth and HPI reduce default risk as borrowers enjoy economic growth and house value growth, while a more substantial contagion effect intensifies the default risk. We plot the default rate and mean PD over time and loan age in Figure 3.7.

Table 3.3: Multinomial logit regression for PD model, empirical analysis

Note: This table presents the multinomial logit (MNL) regression of default/payoff indicator on explanatory variables as specified in Eq. (3.27). The variable definitions are provided in Appendix 3.A. *, ** indicate significance at the 5 percent and 1 percent confidence levels respectively. The coefficients on vintage dummies are not shown for simplicity. The fit statistics include the AUROC and R-squared. The AUROC values are obtained from the probit regressions of the default/payoff indicators on the estimated PD/PP. R-squared is obtained from the MNL regression.

	Default equation		**Payoff equation**	
	Coefficient	Std. Error	Coefficient	Std. Error
DTI	1.782**	0.182	0.292**	0.040
LTV	0.319*	0.156	-0.356**	0.085
FICO	-0.006**	0.000	0.003**	0.000
Orig_Loansize	0.43**	0.064	0.552**	0.042
Mgt insurance	0.712**	0.045	-0.042*	0.019
Investment	0.109*	0.047	-0.408**	0.031

Prepayment penalty	-0.101	0.131	-0.413**	0.041
Multi_borr	-0.576**	0.028	0.157**	0.013
TPO	0.151**	0.021	0.001	0.011
NotSF	0.046	0.035	0.006	0.033
Interest_rate	0.742**	0.025	0.565**	0.026
MSA	-0.264**	0.037	-0.066**	0.021
Age	1.247**	0.049	0.849**	0.015
Age5	-1.069**	0.043	-0.919**	0.012
Age7	-0.027	0.029	0.116**	0.008
Age9	-0.211**	0.029	-0.189**	0.009
Age11	0.047*	0.019	0.151**	0.008
Age13	-0.007	0.039	-0.107**	0.014
HPI_{-1}	-0.005**	0.000	-0.005**	0.001
GDP_Growth_{-1}	-4.005**	0.751	-7.765**	0.775
$Contagion_{-1}$	29.15**	5.99	-13.721**	2.759
Intercept	-14.004**	0.853	-13.079**	0.669
Vintage year dummy	Yes		Yes	
State cluster	Yes		Yes	
AUROC	77.9		72.8	
R-squared	16.12		16.12	
No of observations	33,178,421		33,178,421	

The mean PD closely follows the observed default rate in both charts. The ideal fit between default rate and mean PD substantiates the PD model's accuracy and reassures the compatibility of using it to predict the implied PD for new contracts. This does not change the risk profiles of mortgages. We have analyzed other model alternatives, including logistic regressions, regularization techniques, boosting, and bagging, with consistent results.[73]

[73] We obtain comparable estimation of implied PD across various econometric techniques such as logit model and survival model. Roesch and Scheule (2021) also found that the model performance measured by the AUROC and Brier score are similar among a broader range of classification models for mortgage loans.

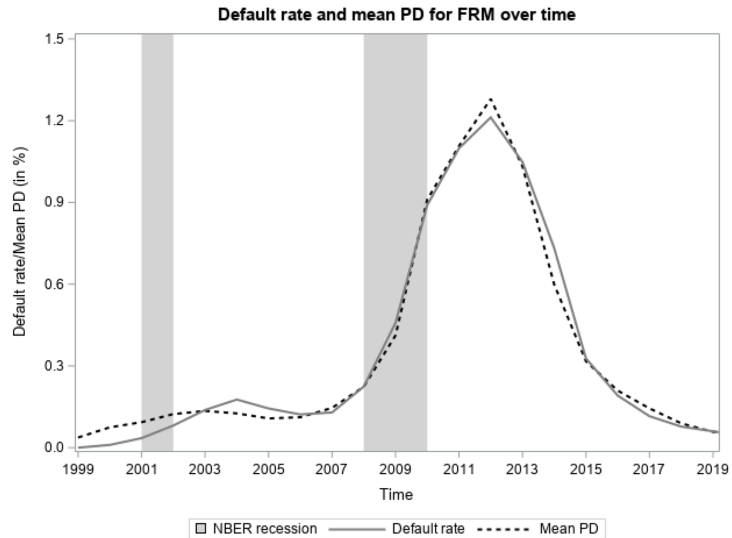

Figure 3.7: Default rate and mean PD for benchmark FRMs, empirical analysis

Note: This figure shows the annual default rate and the mean PD based on multinomial logit regression for the benchmark FRMs from 1999 to 2019 and over loan age. The model is provided in Eq. (3.27). Downturns are defined as NBER recession periods and are indicated by gray columns. The solid line is for the default rate, and the dashed line is for the mean PD. The fit between the default rate and mean PD supports the model's accuracy.

We further estimate a reduced multinomial logit regression estimating the loan indicator on original DTI, loan age and its spline at year 9. The reduced model is applied to adjust the repayment schedule for AFRMs while the comprehensive model is used to measure the implied PD for the various contracts. The reduced model is helpful to simplify repayment schedules.

Repayments are constant for the period before year 9 (i.e., the peak PD) and the period thereafter. More complex repayment schedules are possible but may be harder to communicate to borrowers.[74] Table 3.4 shows that the parameter estimated for the reduced model is aligned with the comprehensive model from Table 3.3. We also run regressions with additional control variables and obtain consistent results for loan age and its spline.

Table 3.4: Multinomial logit regression for AFRMs, empirical analysis

Note: This table presents the results of multinomial logit regression estimating the loan indicator on original DTI, loan age and its spline at year 9. The parameter set from this regression is used to construct they payment growths for AFRMs. *, ** indicate significance at the 5 percent and 1 percent confidence levels respectively. The fit statistics include the AUROC and R-squared. The AUROC values are obtained from the probit regressions of the default/payoff indicators on the estimated PD/PP. R-squared is obtained from the MNL regression.

	Default equation		**Payoff equation**	
	Coefficient	Std. Error	Coefficient	Std. Error
Orig_DTI	3.897**	0.028	0.033**	0.005
Age	0.41**	0.001	0.147**	0.000
Age9	-0.71**	0.004	-0.357**	0.001
Intercept	-8.635**	0.012	-2.243**	0.002
Vintage year dummy		No		No
State cluster		No		No
AUROC		71.5		62.8
R-squared		3.57		3.57
No of observations		33, 178,421		33,178,421

3.4.3 Counterfactual analysis: Updating data features DTI and LTV (Step 3)

The distinction between traditional FRMs and ex-ante contracts lies in the differences in periodic annuities and scheduled balances which change liquidity (DTI) and leverage (LTV). We update the two features based on the contracts (FRMs, DPFRMs, DFRMs, IFRMs, and AFRMs) observed income changes (for DTI) and house prices (for LTV) at the 3-digit zip code level. DTI is updated as follows:

$$\mathrm{DTI}_{it} = \frac{\mathrm{D}_{it}}{\mathrm{I}_{it}} \tag{3.30}$$

[74] There is evidence on limitations of borrowers' knowledge on mortgage terms. See e.g., Bucks and Pence (2008).

t indicates the current period, τ indicates the origination period, D_{it} is the debt payments of the contracts (A for FRMs, ADP for DPFRMs, AD for DFRMs, AI for IFRMs, and AA for AFRMs). I_{it} is the borrower income adjusted by the cumulative income growth at the 3-digit zip code level z:

$$\mathrm{I_{it}} = \mathrm{I_{i\tau}} * \frac{\mathrm{I_{zt}}}{\mathrm{I_{z\tau}}} \tag{3.31}$$

The income at origination is calculated as the FRM annuity over the DTI at loan origination:

$$\mathrm{I_{i\tau}} = \frac{\mathrm{A}}{\mathrm{DTI_{i\tau}}} \tag{3.32}$$

Likewise, LTV is updated as follows:

$$\mathrm{LTV_{it}} = \frac{\mathrm{B_{it}}}{\mathrm{H_{it}}} \tag{3.33}$$

B is the actual loan balance which we assume to be the scheduled balance of the contracts (SB for FRMs, SBDP for DPFRMs, SBD for DFRMs, SBI for IFRMs, and SBA for AFRMs). H_{it} is the borrower house price adjusted by the cumulative house price growth at the 3-digit zip code level z:

$$\mathrm{H_{it}} = \mathrm{H_{i\tau}} * \frac{\mathrm{H_{zt}}}{\mathrm{H_{z\tau}}} \tag{3.34}$$

$\mathrm{H_{zt}}$ is the house price index at observation time t and $\mathrm{H_{z\tau}}$ at origination time τ. The original house price is the original loan balance $\mathrm{B_{i\tau}}$ over the original LTV ratio at loan origination:

$$\mathrm{H_{i\tau}} = \frac{\mathrm{B_{i\tau}}}{\mathrm{LTV_{i\tau}}} \tag{3.35}$$

Figure 3.8 shows the average DTI and LTV for ex-post contracts and FRMs. The results are based on a subsample of loans that originated in 1999 which have the longest history, allowing us to observe the effects of both ex-ante and ex-post adjustments on risk factors.

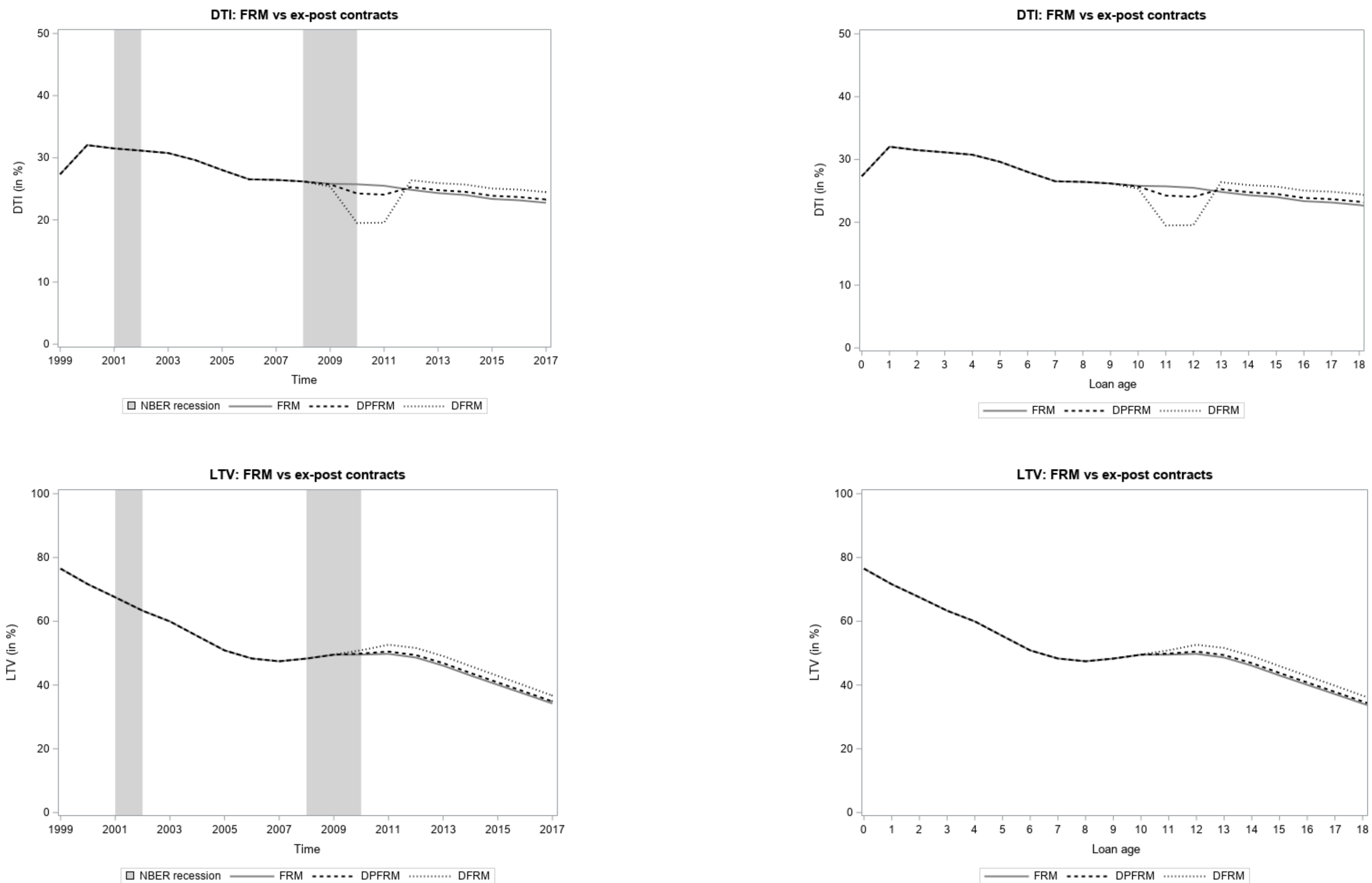

Figure 3.8: DTI and LTV: FRMs and ex-post contracts

Note: This figure shows the differences in DTI (top) and LTV (bottom) over time and loan age between FRMs and ex-post contracts. To offer an apparent variation, we only use the subsample containing loans originating in 1999. The solid line refers to FRMs, the dashed line refers to DPFRMs, and the dotted line refers to DFRMs. Downturns are defined as NBER recession periods and indicated by gray columns.

We set the start of the adjustment period as one year after the beginning of the NBER economic downturn to align with the observed default peak to reflect the delayed recognition of default for delinquent borrowers. Impacts on the mortgage market are usually lagged or delayed compared to the starting point of economic downturns. We apply deferrals to delinquent borrowers for at least 60 days or more as we do not want to distort the repayment plans of good borrowers. The average DTI and LTV of ex-post contracts only divert from those of FRMs during economic downturns as DTIs substantially drop. This fall is considerably larger for DFRMs as borrowers do not have to pay anything during the recession. The amortization process is frozen, increasing average LTVs for these contracts higher than LTVs for FRMs.

Figure 3.9 shows the average DTI and LTV for ex- ante contracts and FRMs. DTI of FRM slowly decreases over loan age. DTIs of IFRMs are generally stable during the loans' lifetimes as repayments increase with income. The DTIs of AFRMs show an inverted hump shape offsetting the hump-shape risk over loan ages.

We notice a difference in average LTVs to the traditional contract. LTVs of IFRMs are constantly higher than for FRMs. This is due to a higher scheduled balance as a trade-off of lower initial payments. The loan balances for AFRMs are significantly higher than for FRMs starting from year 8. The greater loan balance may raise concern for strategic defaults. Note, Gerardi et al. (2018) document that 96 percent of low-equity borrowers with the financial capacity continue servicing their loans. This demonstrates that borrower liquidity dominates borrower equity in importance as a default driver. Bhutta et al. (2017) also argue that borrowers do not walk away from their homes unless they are deeply underwater due to the moral hazard cost of default.[75]

The tradeoff between illiquidity and leverage is stronger for ex-ante contracts than for ex-post contracts. We now continue to examine the impacts of these tradeoffs on the implied model PD.

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[75] See also findings by Ganong and Noel (2022) and Low (2021) on the dominance of illiquidity in triggering default.

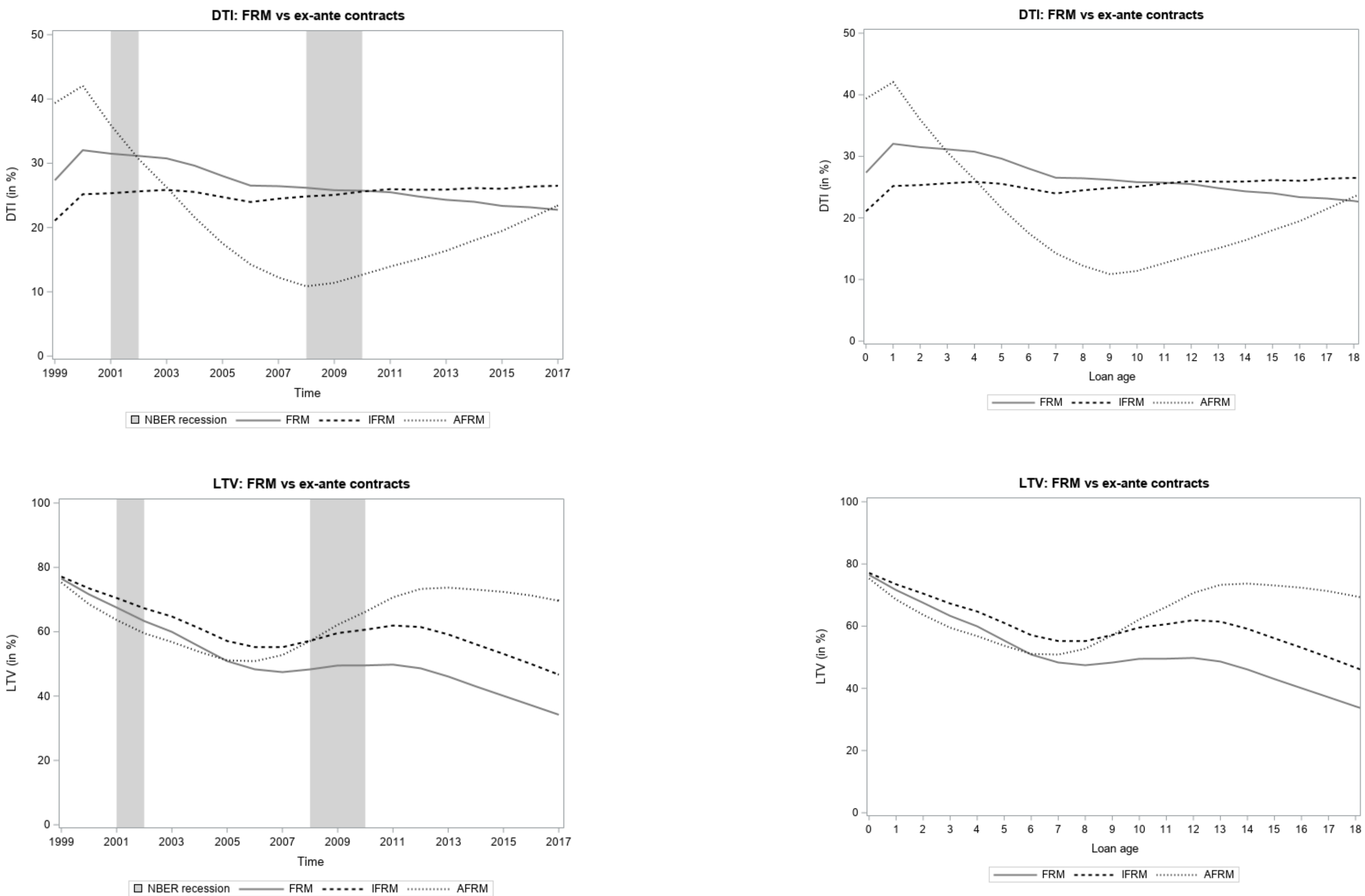

Figure 3.9: DTI and LTV: FRMs and ex-ante contracts

Note: This figure shows the differences in DTI (top) and LTV (bottom) over time and loan age between FRMs and ex-ante contracts. To offer an apparent variation, we only use the subsample containing loans originating in 1999. The solid line refers to FRMs, the dashed line refers to IFRMs, and the dotted line refers to AFRMs. Downturns are defined as NBER recession periods and are indicated by gray columns.

3.4.4 Proxying default risk with model-implied default probabilities (Step 4)

After estimating the PD model based on observed data for FRMs at the first step, we obtain the parameter set. We then replace the DTI and LTV with the corresponding values from the new designs and fit the implied PD using this parameter set. Note that we retain all other factors. We plot the mean PD for FRMs and ex-post contracts over time and loan age in Figure 3.10.

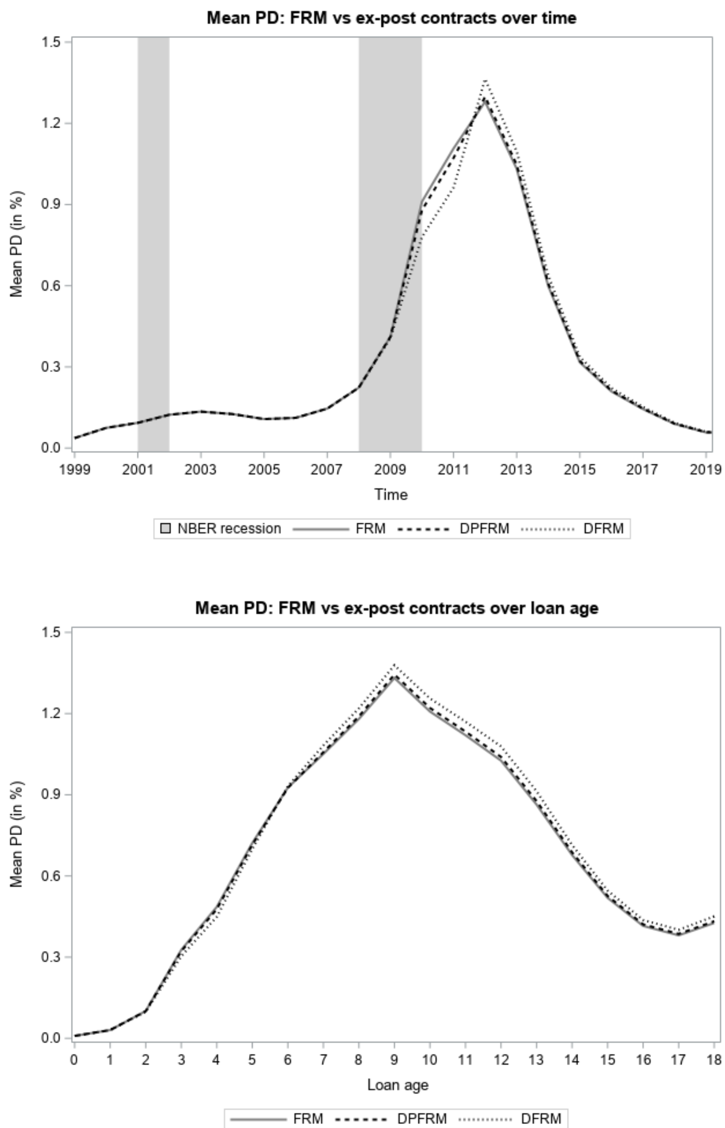

Figure 3.10: Mean PD – FRMs vs. ex-post contracts, empirical analysis

Note: This figure shows the differences in mean PD between FRMs and ex-post contracts from 1999 to 2019 and over loan age. The model to estimate the PD of FRMs is provided in Eq. (3.27). The implied PDs for ex-post contracts are calculated after updating DTI and LTV values. Downturns are defined as NBER recession periods and are indicated by gray columns. The top chart shows the difference over time. The bottom shows the difference over loan age. The solid lines are for the mean PD of FRMs; the dashed lines are the mean implied PD of DPFRMs; the dotted lines are the mean implied PD of DFRMs.

The effects of DPFRMs are almost negligible as there are smaller gaps between mean PD and default rate at the peak compared to FRMs. DFRMs on the other hand have more potent effects. We notice the reductions in mean PD in 2010 and 2011 when the deferment is implemented. However, this does not curtail the peak default risk. The peak PD of DFRMs exceed that of FRMs in 2012, indicating an increase in systematic risk. Longer periods of more than two years may help to reduce the default risk. However, lenders often offer liquidity relief for only up to six months or a year. Therefore, using ad-hoc ex-post adjustments could be expensive and inefficient in dealing with default risk. The mean PD by loan age also indicates a level of weakness in ex-post contracts when attempting to reduce default risk, as there is no risk shrinkage during the period when borrowers are likely to face the highest financial stress.

We plot the mean PD over time and loan age for ex-ante contracts in Figure 3.11. There are downward shifts (from the solid line for FRMs to the dashed line of IFRMs and the dotted line of AFRMs) in the mean PD over time. Significantly, the drop is strongest at the peak PD. This indicates a reduction in financial fragility if these contracts are adopted. The PD improvements for AFRMs are more substantial than IFRMs. The former is designed to lessen the adverse shocks over borrower life cycles by providing payment relief. The latter only considers the alignment of repayments to borrower income growth. Implementing the AFRMs model may be easier as the age-risk profile is less time-variant than income growth and hence more predictable.[76]

[76] The univariate t-tests on means of income growth, k1 and k2 between upturn and downturn periods show that the difference in means of income growth is more statistically significant than that of k growths. Upturn period is when annual default rate is lower than overall mean PD and downturn period is when annual default rate is higher than overall mean PD.

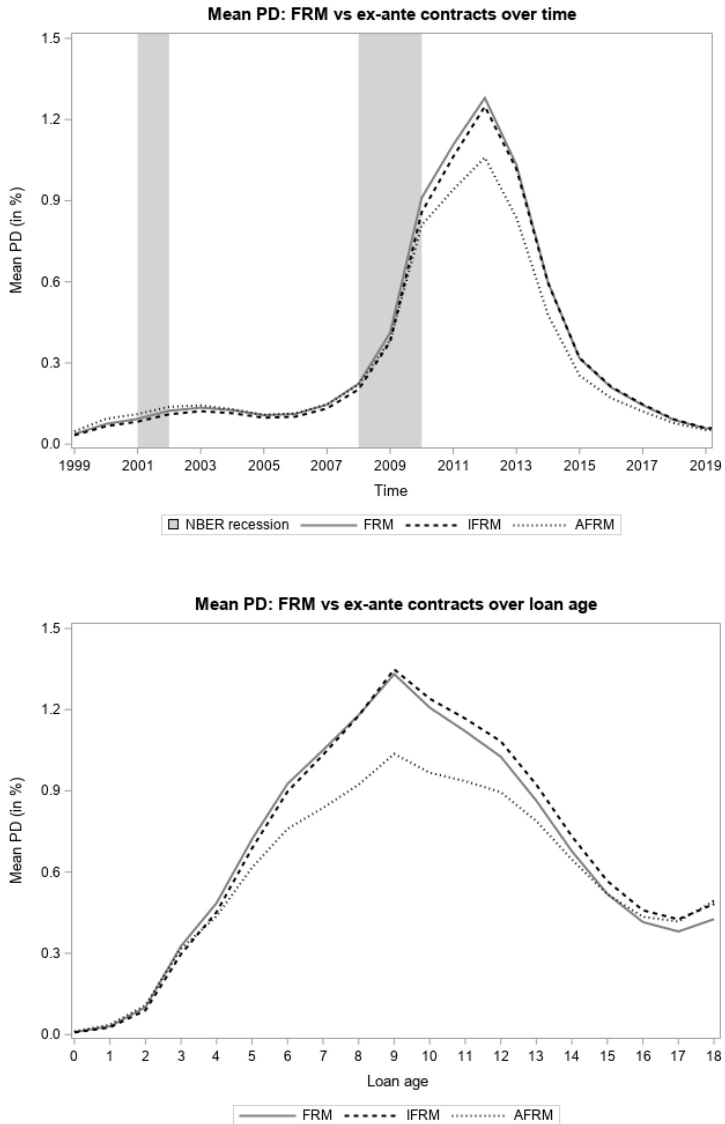

Figure 3.11: Mean PD – FRMs vs. ex-ante contracts, empirical analysis

Note: This figure shows the differences in mean PD between FRMs and ex-ante contracts from 1999 to 2019 and over loan age. The model to estimate the PD of FRMs is provided in Eq. (3.27). The implied PDs for ex-ante contracts are calculated after updating DTI and LTV values. Downturns are defined as NBER recession periods and are indicated by gray columns. The top chart shows the difference over time. The bottom shows the difference over loan age. The solid lines are for the mean PD of FRMs; the dashed lines are the mean implied PD of IFRMs; the dotted lines are the mean implied PD of AFRMs.

The graphs based on loan age show that AFRMs significantly lower borrower financial stress during the peak time. The effects of IFRMs are similar to FRMs, but the risk is slightly shifted to the later period of the loan life. IFRMs generate a higher default rate immediately after year

9 and AFRMs increase the risk when loans are more mature (i.e., older than 15 years).

3.4.5 Impact analysis (Step 5)

3.4.5.1 Mean PD, systematic risk, and regulatory capital

We now calculate each contract's mean PD, systematic risk and regulatory capital and make a comparison. The mean PD is the average PD over the entire sample. Systematic risk and regulatory capital are measured using Basel regulations (Basel Committee on Banking Supervision, 2005). The systematic risk is measured as the difference between the maximum mean PD over time and the mean PD. The regulatory capital is computed via Eq (20):

$$\mathrm{RC_{it}} = \mathrm{LGD_{it}}\left[\Phi\left(\frac{\Phi^{-1}(\mathrm{PD})+\sqrt{\rho}\Phi^{-1}(0.999)}{\sqrt{1-\rho}}\right) - \mathrm{PD_{it}}\right] \tag{3.36}$$

where Φ is the CDF of the standard normal distribution t and Φ^{-1} its inverse, ρ is the regulatory AC with a regulatory setting of 15 percent for residential mortgages, and PD is the mean PD calculated over the full sample for each contract. We use the Downturn LGD estimated from the mortgage data at 61.34 percent to highlight the difference in capital level between FRMs and the proposed contract designs.[77] We use a confidence level of 99.9 percent in the capital formula, which is common in banking and the basis of the Basel regulations.

Regulatory capital is the minimum level of capital required by the regulator and is based on risk weighted assets held by the organization. The main function of this requirement is to absorb potential losses through a buffer. The calculation of minimum regulatory capital relies heavily on bank-internal measures for PD and LGD. At the same time, the product of PD and LGD – the expected loss – is a crucial component of the mortgage interest rate (Phillips, 2018). As a result, regulatory capital influences the interest rate charged on mortgages. This increase in capital can then lead to a subsequent increase in lender costs (Baker & Wurgler, 2015).

[77] The derivation of Downturn LGD is provided in Appendix 2.F.

We summarize mean PD, systematic risk, and regulatory capital results in Panel A of Table 3.5 for the entire sample, expressing the impacts of new contracts from the perspective of the market portfolio. The effects of ex-post contracts are negligible in reducing mean PD. DFRMs are stronger than DPFRMs, but the full deferment option helps to bring down the mean PD by 0.8 percent. Conversely, ex-post contracts escalate the systematic risk with increments of 2 percent for DPFRMs and 9.2 percent for DFRMs. We observe a slight drop in the regulatory capital, but the relative reductions are only 0.1 percent for DPFRMs and 0.5 percent for DFRMs.

Table 3.5: Main analysis on risk and economic impacts of new contracts

Note: This table reports the risk impact and economic impact of new contracts. Panel A shows Mean PD, systematic risk, and regulatory capital. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum PD) and Mean PD. Regulatory capital is calculated using Basel regulation. Panel B shows ROC, new spread, and cumulative interest ratio. ROC is the ratio between credit spread and regulatory capital. The credit spread equals to interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals to ROC of FRMs multiplying regulatory capital. A cumulative interest ratio equals total nominal interest dividing the original loan balance. The interest payments are calculated with the revised interest rate which equals to the current interest rate on FRMs minus the credit spread savings (the absolute change in new spread between FRMs and other contracts). We show the absolute change and relative change between FRMs with ex-post and ex-ante contracts for each item. The results are calculated using the full sample with 33,197,738 observations. All values are expressed as percentages.

Panel A: Risk impact

		Ex-post contracts		Ex-ante contracts	
	FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD	0.342	0.341	0.339	0.330	0.297
Abs change		-0.001	-0.003	-0.012	-0.044
Rel change		-0.202	-0.864	-3.446	-12.996
Systematic risk	0.928	0.946	1.010	0.908	0.759
Abs change		0.018	0.083	-0.020	-0.169
Rel change		1.962	8.904	-2.124	-18.217
Regulatory capital	3.001	2.997	2.982	2.926	2.713
Abs change		-0.004	-0.019	-0.075	-0.288
Rel change		-0.147	-0.626	-2.502	-9.600

Panel B: Economic impact

		Ex-post contracts		Ex-ante contracts	
	FRM	DPFRM	DFRM	IFRM	AFRM
ROC	58.911	58.996	59.281	60.422	65.165
Abs change		0.085	0.370	1.511	6.254
Rel change		0.144	0.628	2.565	10.616
New spread	1.768	1.765	1.757	1.724	1.598
Abs change		-0.003	-0.011	-0.044	-0.170
Rel change		-0.147	-0.626	-2.502	-9.600
Cumulative interest ratio	95.527	97.650	101.087	113.063	127.754
Abs change		2.124	5.560	17.536	32.227
Rel change		2.223	5.820	18.358	33.736

The impacts of ex-ante contracts are more substantial. For IFRMs, we detect a lower mean PD by 1.2 bps, equivalent to a drop of 3.5 percent. This effect is three times stronger for AFRMs, within which the mean PD can be lowered by 4.5 bps or 13 percent. The age-related contract is also superior to the income-based design in reducing systematic risk. The risk reduction follows on to a cut in regulatory capital. AFRMs generate a relative decrease in capital cost of almost 10 percent, and this drop for IFRMs is approximately 3 percent.

3.4.5.2 Return-on-capital ratio and new credit spread

We examine the ROC ratio and new spread to evaluate the economic impact of new contracts in Panel B of Table 3.5. We calculate the ROC ratio by dividing the credit spread by regulatory capital. AFRMs are best for enhancing the return ratio with a relative change of more than 10 percent, followed by IFRMs with an increase of 2.6 percent. The increases in ex-post contracts are minimal. These gains are due to the capital cost reductions from the new models.

The new spread is calculated for new contracts as the ROC of FRMs multiplying the regulatory capital. Due to capital cost reductions, lenders could obtain a higher return ratio. Alternatively, lenders may offer more competitive interest rates while maintaining return levels. In other words, borrowers may benefit from a lower credit spread of 17 bps or 10 percent in competitive markets. The benefit created by IFRMs is roughly five bps, equivalent to a drop of 2.6 percent. Borrowers of ex-post contracts may experience a drop of 1 bp in credit spreads.

Are borrowers exposed to larger loan amounts and do they pay more interest over loan lifetimes? We inspect the cumulative interest ratio by dividing the total hypothetical interest payment by the original loan balance for ex-ante contracts. The average ratio is 100 percent for FRMs, 116 percent for IFRMs, and 146 percent for AFRMs. The total interest payment of IFRM borrowers increases by 16 percent and AFRM borrowers increases by 46 percent. Even though the new contracts induce lower credit spreads, there are expansions in scheduled balances, resulting in higher interest payments. Despite that, we need to reinforce the effect of ex-ante contracts in reducing risk and improving financial resilience. Borrowers continue to have prepayment rights and may prepay earlier at any time.

In short, the portfolio-wide risk reductions are higher in the ex-ante contracts than ex-post contracts. The former's impact is also more vital than the latter in enhancing the return ratio and generating a lower credit spread. AFRMs provide the highest financial resilience of all contracts studied.

3.4.6 Sub-sample analysis

3.4.6.1 Bank and nonbank subsamples

As banks and nonbanks are subject to different lending standards and regulatory burdens, we analyze these two sub-samples and present the results in Table 3.6.

Nonbank mortgages have a higher risk than banks, indicated by a higher mean PD, systematic risk, and regulatory capital. Due to the homogeneity and concentration of nonbank loan portfolios, nonbank mortgages become riskier than their counterpart. The findings are consistent with the primary analysis regarding the effects of new contracts for the two sub-samples. Ex-ante contracts are better than ex-post contracts in reducing risk and capital costs, enhancing the return ratio, or deducting credit spread. The effect magnitudes are slightly stronger for the nonbank sub-sample. We choose mortgages originated by Wells Fargo and those originated by Countrywide home loans as the representatives for banks and nonbanks and replicate the analysis. All findings re-confirm that nonbank lenders may benefit more from the new designs.

3.4.6.2 Upturn and downturn periods

The next robustness test is for upturn and downturn periods. The upturn sample includes mortgage performances before 2010 and after 2014, and the downturn sample includes the periods between these years. The default rate is lower than the median value during the upturn sample, and the downturn sample includes default rates higher than the median value. Mortgages are likely more sensitive to systematic risk factors during downturns than upturns. As a result, the impacts of new designs could vary with the macroeconomy. Table 3.7 presents the results of the upturn and downturn analysis.

Table 3.6: Analysis on risk and economic impacts of new contracts for banks and nonbanks

Note: This table reports the analysis for bank and nonbank subsamples including the absolute change and relative change in Mean PD, systematic risk, regulatory capital, ROC, and new spread between FRMs and other contracts. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum PD) and Mean PD. Regulatory capital is calculated using Basel regulation. ROC is the ratio between credit spread and regulatory capital. The credit spread equals to interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals to ROC of FRMs multiplying regulatory capital. The bank subsample has 6,834,903 observations and the nonbank subsample has 17,262,484 observations. We also replicate the analysis for two representatives of banks and nonbanks, which are Wells Fargo and Countrywide to further clarify the difference between banks and nonbanks. The result is presented in Appendix 3.C. All values are expressed as percentages.

	Banks					Nonbanks				
	FRM	DPFRM	DFRM	IFRM	AFRM	FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD	0.379	0.378	0.375	0.366	0.330	0.410	0.409	0.405	0.395	0.355
Abs change		-0.001	-0.004	-0.013	-0.049		-0.001	-0.005	-0.015	-0.055
Rel change		-0.264	-1.055	-3.430	-12.929		-0.244	-1.220	-3.659	-13.415
Systematic risk	0.844	0.861	0.921	0.827	0.691	1.580	1.614	1.730	1.541	1.293
Abs change		0.017	0.077	-0.017	-0.153		0.034	0.150	-0.039	-0.287
Rel change		2.014	9.123	-2.014	-18.128		2.152	9.494	-2.468	-18.165
Regulatory capital	3.232	3.226	3.210	3.153	2.927	3.418	3.412	3.391	3.333	3.084
Abs change		-0.006	-0.022	-0.079	-0.305		-0.006	-0.027	-0.085	-0.334
Rel change		-0.186	-0.681	-2.444	-9.437		-0.176	-0.790	-2.487	-9.772
ROC	54.142	54.228	54.505	55.485	59.771	54.052	54.147	54.479	55.443	59.909
Abs change		0.086	0.363	1.343	5.629		0.095	0.427	1.391	5.857
Rel change		0.159	0.670	2.481	10.397		0.176	0.790	2.573	10.836
New spread	1.750	1.747	1.738	1.707	1.585	1.848	1.844	1.833	1.802	1.667
Abs change		-0.003	-0.012	-0.043	-0.165		-0.003	-0.015	-0.046	-0.181
Rel change		-0.172	-0.667	-2.431	-9.424		-0.185	-0.799	-2.496	-9.780

Table 3.7: Analysis on risk and economic impacts of new contracts for upturn and downturn periods

Note: This table reports the analysis for upturn and downturn subsamples including the absolute change and relative change in Mean PD, systematic risk, regulatory capital, ROC, and new spread between FRMs and other contracts. The upturn subsample includes observations before 2009 and after 2014 and the downturn subsample includes observations from 2009 to 2014. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum PD) and Mean PD. Regulatory capital is calculated using Basel regulation. ROC is the ratio between credit spread and regulatory capital. The credit spread equals to interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals to ROC of FRMs multiplying regulatory capital. The upturn subsample has 23,815,254 observations and the downturn subsample has 9,382,484 observations. All values are expressed as percentages.

	Upturn periods					Downturn periods				
	FRM	DPFRM	DFRM	IFRM	AFRM	FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD	0.130	0.131	0.134	0.126	0.119	0.879	0.874	0.859	0.848	0.750
Abs change		0.001	0.004	-0.004	-0.011		-0.005	-0.020	-0.031	-0.129
Rel change		0.769	3.077	-3.077	-8.462		-0.569	-2.275	-3.527	-14.676
Systematic risk	0.188	0.192	0.203	0.194	0.138	0.390	0.413	0.490	0.390	0.306
Abs change		0.004	0.015	0.006	-0.050		0.023	0.100	0.000	-0.084
Rel change		2.128	7.979	3.191	-26.596		5.897	25.641	0.000	-21.538
Regulatory capital	1.464	1.472	1.496	1.429	1.367	5.807	5.785	5.717	5.667	5.216
Abs change		0.008	0.032	-0.035	-0.097		-0.022	-0.090	-0.140	-0.591
Rel change		0.546	2.186	-2.391	-6.626		-0.379	-1.550	-2.411	-10.177
ROC	118.345	117.662	115.758	121.179	126.713	31.892	32.014	32.394	32.681	35.504
Abs change		-0.683	-2.587	2.834	8.368		0.122	0.502	0.789	3.612
Rel change		-0.577	-2.186	2.395	7.071		0.383	1.574	2.474	11.326
New spread	1.732	1.742	1.770	1.691	1.618	1.852	1.845	1.823	1.807	1.663
Abs change		0.010	0.038	-0.041	-0.114		-0.007	-0.029	-0.045	-0.188
Rel change		0.577	2.217	-2.361	-6.597		-0.374	-1.545	-2.406	-10.173

The findings are consistent with the main analysis. The effects of new designs regarding the relative changes from the traditional FRMs are generally stronger for downturn periods than upturn periods. Except for the systematic risk, the reductions in mean PD and regulatory capital generated from the former results are doubled compared to the latter. PD variations are larger and result in greater systematic risk during downturns.

3.4.6.3 Risk classes

We bin the original PD estimations into ten risk classes assuming an equal number of default observations so that parameter estimates have lower standard errors and models are more robust.[78] The default rate and original PD monotonically increase from the lowest-risk to the highest-risk class. We expect that the impacts of new designs in reducing risk and improving return may vary across risk classes. Table 3.8 summarizes the relative change in mean PD, systematic risk, regulatory capital, ROC, and new spread for each risk class.

Ex-post contracts help to reduce mean PD and regulatory capital but increase systematic risk. These risk reductions lead to a rise in ROC and a fall in credit spread. We notice that the effects of ex-post contracts are more potent for higher-risk classes. Ex-post contracts aim to mitigate the default risk for delinquent loans, which are usually considered riskier than others.

Ex-ante contracts dominate in risk reduction and return enhancement. We observe decreases in mean PD, systematic risk, regulatory capital, and credit spread and increases in ROC. Looking closely into the risk classes, we find that the effects of IFRMs are strongest for the lowest-risk class, while AFRMs exert more profound effects on mortgages in medium and high-risk classes. The income growth used for FRMs is not related to the borrower’s risk; hence the risk reduction effects cannot exert an impact on the high-risk loans. In contrast, AFRMs are closely linked to the age-related risk profile and aim to offset the risk profile, so the effects on higher-risk loans are more compelling.

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[78] We provide the description of risk class formation in Appendix 3.D.

Table 3.8: Analysis on risk and economic impacts of new contracts for risk classes

Note: This table reports the analysis for risk classes including Mean PD, systematic risk, regulatory capital, ROC, and new spread between FRMs and other contracts. The description of risk classes is provided in Appendix 3.D. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum PD) and Mean PD. Regulatory capital is calculated using Basel regulation. ROC is the ratio between credit spread and regulatory capital. The credit spread equals interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals ROC of FRMs multiplying regulatory capital. We show the relative changes in each item. The last row of each panel shows the average value across risk classes. All numbers are expressed as percentages.

	DPFRM					**DFRM**				
Risk class	Mean PD	Sys. Risk	Reg. Capital	ROC	New spread	Mean PD	Sys. Risk	Reg. Capital	ROC	New spread
Lowest risk	0.000	0.000	-0.104	0.025	-0.071	0.000	2.239	-0.104	0.045	-0.071
2	0.000	1.192	-0.030	0.048	-0.038	-0.254	4.768	-0.120	0.117	-0.129
3	0.000	1.411	-0.045	0.060	-0.051	-0.169	5.892	-0.135	0.150	-0.141
4	-0.122	1.707	-0.072	0.071	-0.068	-0.245	7.143	-0.163	0.165	-0.159
5	-0.093	1.951	-0.090	0.077	-0.083	-0.278	8.204	-0.225	0.215	-0.218
6	-0.140	2.288	-0.100	0.095	-0.097	-0.421	9.635	-0.313	0.305	-0.311
7	-0.160	2.586	-0.116	0.112	-0.115	-0.641	11.079	-0.391	0.390	-0.389
8	-0.238	3.065	-0.150	0.147	-0.148	-1.029	13.266	-0.598	0.601	-0.597
9	-0.368	3.516	-0.203	0.206	-0.204	-1.698	15.421	-0.943	0.954	-0.944
Highest risk	-0.692	4.738	-0.340	0.346	-0.342	-3.863	22.202	-1.914	1.954	-1.916
Average	**-0.181**	**2.245**	**-0.125**	**0.119**	**-0.122**	**-0.860**	**9.985**	**-0.491**	**0.490**	**-0.487**

	IFRM					**AFRM**				
	Mean PD	Sys. Risk	Reg. Capital	ROC	New spread	Mean PD	Sys. Risk	Reg. Capital	ROC	New spread
Lowest risk	-5.333	-2.239	-3.553	3.684	-3.520	-10.667	-16.418	-8.255	8.950	-8.224
2	-3.299	0.954	-2.347	2.397	-2.355	-12.183	-20.858	-8.968	9.857	-8.975
3	-3.209	0.581	-2.234	2.284	-2.240	-13.007	-21.494	-9.253	10.205	-9.258
4	-3.060	0.190	-2.153	2.188	-2.149	-13.464	-21.745	-9.390	10.370	-9.387
5	-3.053	-0.150	-2.085	2.123	-2.079	-13.784	-22.011	-9.406	10.373	-9.400
6	-3.088	-0.401	-2.018	2.062	-2.015	-14.035	-22.200	-9.302	10.259	-9.299
7	-3.153	-0.607	-1.964	2.007	-1.963	-14.110	-22.222	-9.092	10.006	-9.091
8	-3.246	-0.736	-1.936	1.977	-1.935	-14.212	-22.364	-8.784	9.629	-8.782
9	-3.367	-0.824	-1.900	1.939	-1.901	-13.922	-22.326	-8.157	8.883	-8.158
Highest risk	-3.573	-0.924	-1.763	1.797	-1.765	-12.860	-17.420	-6.609	7.078	-6.611
Average	**-3.438**	**-0.416**	**-2.195**	**2.246**	**-2.192**	**-13.224**	**-20.906**	**-8.722**	**9.561**	**-8.719**

These findings reinforce that AFRMs are a better option for lenders in a more volatile market. Through the risk-class analysis, we state that AFRMs are the most effective designs in inducing greater financial resilience. Adopting AFRMs can concurrently reduce mean PD, systematic risks, capital costs and mortgage spreads. Return ratios are consequently enhanced.

3.5 Robustness tests

3.5.1 Contract variations

We provide a number of variations for ex-ante contracts. The AFRM may provide borrowers with excessive liquidity mortgage payment decreases in initial years (i.e., pre-peak period) or lenders may not be comfortable with lowering mortgage payments over time. Hence, we analyse a hybrid FRM (HFRM) contract with constant repayments until the peak risk year and increasing repayments thereafter. HFRM combines elements of FRM, IFRM and AFRM contracts.[79] The first repayment of HFRM (AH), scheduled payments (SPH), and the scheduled balance (SBH) can be calculated as follows:

$$\mathrm{AH} = \frac{\mathrm{B}(1+\mathrm{i})^{\mathrm{p}}}{\mathrm{PV}_1(1+\mathrm{i})^{\mathrm{p}}+\mathrm{PV}_2(1+\mathrm{k})} \tag{3.37}$$

where $\mathrm{PV1} = \frac{1}{\mathrm{i}} - \frac{1}{\mathrm{i}}\left(\frac{1}{1+\mathrm{i}}\right)^{\mathrm{p}}$ and $\mathrm{PV2} = \frac{1}{\mathrm{i}-\mathrm{k2}} - \frac{1}{\mathrm{i}-\mathrm{k2}}\left(\frac{1+\mathrm{k2}}{1+\mathrm{i}}\right)^{(\mathrm{n}-\mathrm{p})}$

$$\mathrm{SPH}_{\mathrm{t}} = \begin{cases} \mathrm{AH} & \text{if } \mathrm{t} \leq \mathrm{p} \\ \mathrm{AH}(1+\mathrm{k})^{\mathrm{t}-\mathrm{p}} & \text{if } \mathrm{t} > \mathrm{p} \end{cases} \tag{3.38}$$

$$\mathrm{SBH}_{\mathrm{t}} = \mathrm{B}(1+\mathrm{i})^{\mathrm{t}} - \textstyle\sum_{\mathrm{t}=1}^{\mathrm{n}} \mathrm{SPH}_{\mathrm{t}}(1+\mathrm{i})^{\mathrm{t}-1} \tag{3.39}$$

where B is the loan balance, k is the growth rate of HFRM equal to k_2 of the AFRM, p is the peak time (i.e., year 9), and i is the contract rate.

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[79] We thank the participants from various seminars and conferences as well as multiple anonymous reviewers and examiners for raising the interest for such as contract.

We compare annual repayments and the scheduled balance of HFRM with FRM in Figure 3.12. The plot is based on an example loan with an original balance of \$100,000, an interest rate of 5 percent, a maturity of 30 years, and k is 10 percent.

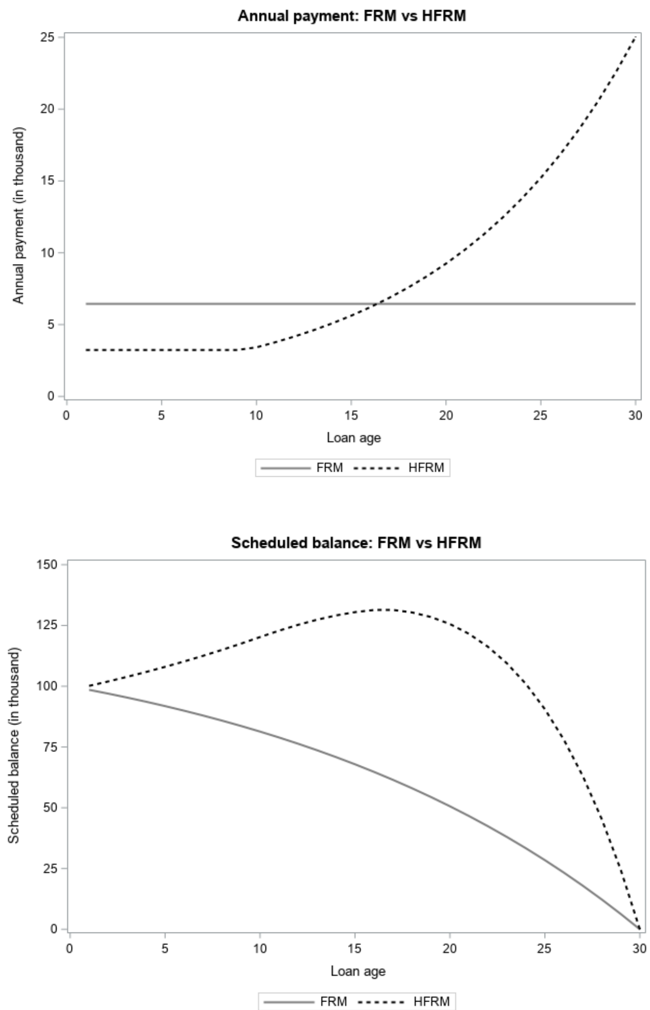


Figure 3.12 Monthly payment and scheduled balance: FRMs vs. HFRMs

Note: This figure shows the monthly payments (top) and the scheduled loan balances (below) of the hybrid fixed-rate mortgage and a benchmark fixed-rate mortgage contract for an example loan. The solid line refers to FRMs, and the dashed line refers to HFRMs. For FRMs, the periodic payment is computed by Eq. (3.1) and the scheduled balance is computed by Eq. (3.2). For HFRMs, the periodic payments are computed by Eq. (3.38) and the scheduled balance is computed by Eq. (3.39). These calculations are done at a monthly frequency. We take the sum of all monthly periodic payments as the annual payment and take the last value of scheduled balance as the annual scheduled balance. The example loan's amount at origination is 100,000, the contract rate is 5 percent, and the time to maturity at loan origination is 30 years. We use the growth rate k of 10 percent (p. a.) which is the same as k_2 as in the later regime of AFRM to calculate the periodic payment and scheduled balance for HFRMs.

The second variation halves growth ratios relative to the original IFRM contracts. This contract may be relevant for a transitionary implementation of the corresponding proposed design. The third variation changes the growth calculation: We use income growth at the zip code level to construct IFRMs. The fourth variation halves growth ratios relative to the original AFRM contracts. Again, this contract may be relevant for transitionary implementation. The fifth variation analyses age-related payment growth based on an extrapolation of over 30 years for AFRMs. We replicate the impact analysis for all five alternative ex-ante contracts and present the results in Table 3.9.

Table 3.9: Robustness test: alternative ex-ante contracts

Note: This table reports the analysis for alternative ex-ante contracts including the absolute change and relative change in Mean PD, systematic risk, regulatory capital, ROC, and new spread between FRM, and other contracts. HFRM is the hybrid FRM where repayment remains constant in the first 9 years and increases with the same growth rate as AFRM afterward. IFRM, ½ growth is constructed using ½ income growth at the state level. IFRM, zip code's income growth is constructed using the income growth at the zip code level. AFRM, ½ growth is constructed using a half of k_1 and k_2. AFRM, 30-year extrapolation is constructed using the k factors estimated with 30-year extrapolated data. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum among mean PD over time) and Mean PD. Regulatory capital is calculated using Basel regulation. ROC is the ratio between credit spread and regulatory capital. The credit spread equals interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals ROC of FRMs multiplying regulatory capital. All values are expressed as percentages.

	FRM	**HFRM**	**IFRM, 1/2 growth**	**IFRM, zip code's income growth**	**AFRM, 1/2 growth**	**AFRM, 30-year extrapolation**
Mean PD	0.342	0.299	0.336	0.327	0.318	0.281
Abs change		-0.043	-0.006	-0.015	-0.024	-0.060
Rel change		-12.623	-1.735	-4.351	-6.898	-17.697
Systematic risk	0.928	0.815	0.919	0.901	0.835	0.710
Abs change		-0.113	-0.008	-0.027	-0.093	-0.218
Rel change		-12.134	-0.895	-2.900	-10.003	-23.521
Reg. capital	3.001	2.723	2.963	2.906	2.850	2.605
Abs change		-0.278	-0.038	-0.095	-0.151	-0.396
Rel change		-9.267	-1.256	-3.166	-5.038	-13.185
ROC	58.843	64.855	59.592	60.766	61.965	67.780
Abs change		6.012	0.749	1.923	3.122	8.937
Rel change		10.217	1.273	3.268	5.306	15.188
New spread	1.766	1.604	1.744	1.710	1.677	1.533
Abs change		-0.162	-0.022	-0.056	-0.089	-0.233
Rel change		-9.168	-1.254	-3.163	-5.036	-13.183

Compared to FRM, the adoption of a hybrid contract yields significant advantages, reducing the mean PD by 12.6 percent and decreasing systematic risk by 12.1 percent. These reductions translate to a 9.3 percent decrease in regulatory capital requirements or a 10.2 percent increase in ROC. Otherwise, the HFRM borrowers can enjoy a drop of 9.2 percent equivalent to 16.2 bps on their mortgages. When compared to the original ex-ante contracts, the performance of HFRMs is on par.

In the second and fourth variations where the growth rates are scaled down as half of the original rates, the adoptions of IFRM and AFRM can still lead to risk reduction and return improvement. The relative changes in the reduction of regulatory capital are recorded at 1.3 percent for IFRM and 5 percent for AFRM, which are roughly half of the effects of the origination models. Personalized AFRMs continue to outperform personalized IFRMs.

In the third and fifth variations where growth rates are estimated differently, the effects of ex-ante contracts generate even more substantial effects compared to the original designs. The IFRM's income growth estimated at the zip code level registers at 3.3 percent, surpassing the 2.5 percent at the state level. This leads to a drop of 3.2 percent in regulatory capital and a rise of 3.3 percent in the ROC ratio, indicating a stronger effect than the IFRMs with the state-based income growth rate. The age-related growth rates from the 30-year extrapolation are also higher than those from the 21-year span. In specific, k_1 increases from -15 percent to -24 percent and k_2 increases from 11 percent to 17 percent. This leads to a 3 percent higher in regulatory capital and 5 percent higher in ROC with the adoption of AFRMs. Overall, these variations serve to reinforce the overall impact and effectiveness of the ex-ante strategies.

3.5.2 Using logit regression

Our main analysis employs multinomial logit regression to estimate the PD model to control selection of competing risks. We acknowledge that logit regressions are widely used in the mortgage industry; hence we provide the analysis using the logit model in Panel A of Table 3.10. The effects are consistent with the main analysis in both signs and magnitudes.

Table 3.10: Robustness tests

Note: This table reports the risk impact and economic impact of new contracts using different PD models. In Panel A, we replicate the analysis with the logit model. In Panel B, we replicate the analysis with the sample of mortgages having loan age shorter than 10 years. In Panel C, we replicate the analysis with the full sample. All values are expressed as percentages.

		FRM	DPFRM	DFRM	IFRM	AFRM
Panel A: Analysis using Logit regression						
Mean PD		0.342	0.341	0.338	0.329	0.297
	Abs change		-0.001	-0.003	-0.013	-0.045
	Rel change		-0.230	-0.969	-3.833	-13.082
Systematic risk		0.924	0.942	1.005	0.901	0.755
	Abs change		0.018	0.080	-0.024	-0.169
	Rel change		1.926	8.698	-2.553	-18.315
Regulatory capital		3.001	2.996	2.980	2.917	2.711
	Abs change		-0.005	-0.021	-0.084	-0.290
	Rel change		-0.167	-0.700	-2.786	-9.663
ROC		58.845	58.943	59.260	60.531	65.139
	Abs change		0.098	0.415	1.686	6.294
	Rel change		0.167	0.705	2.865	10.696
New spread		1.766	1.763	1.754	1.717	1.595
	Abs change		-0.003	-0.012	-0.049	-0.171
	Rel change		-0.164	-0.698	-2.784	-9.661
Panel B: Analysis with shorter data history (10 years)						
		FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD		0.324	0.323	0.319	0.310	0.282
	Abs change		-0.001	-0.004	-0.013	-0.042
	Rel change		-0.328	-1.378	-4.146	-12.924
Systematic risk		0.927	0.945	1.008	0.907	0.761
	Abs change		0.018	0.082	-0.019	-0.165
	Rel change		1.943	8.817	-2.094	-17.829
Regulatory capital		2.887	2.880	2.858	2.799	2.610
	Abs change		-0.007	-0.029	-0.087	-0.276
	Rel change		-0.236	-1.001	-3.024	-9.572
ROC		60.380	60.524	60.990	62.262	66.772
	Abs change		0.144	0.610	1.882	6.392
	Rel change		0.238	1.010	3.117	10.586
New spread		1.743	1.739	1.725	1.690	1.576
	Abs change		-0.004	-0.017	-0.053	-0.167
	Rel change		-0.234	-1.000	-3.023	-9.570
Panel C: Analysis using the full sample						
		FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD		0.322	0.319	0.317	0.315	0.284
	Abs change		-0.002	-0.004	-0.007	-0.037
	Rel change		-0.644	-1.372	-2.100	-11.533
Systematic risk		0.892	0.898	0.954	0.889	0.755
	Abs change		0.006	0.063	-0.003	-0.137
	Rel change		0.694	7.022	-0.325	-15.361
Regulatory capital		2.871	2.858	2.843	2.828	2.627

	Abs change		-0.013	-0.029	-0.044	-0.245
	Rel change		-0.467	-0.996	-1.529	-8.525
ROC		60.701	60.985	61.311	61.642	66.357
	Abs change		0.284	0.610	0.941	5.656
	Rel change		0.468	1.005	1.550	9.318
New spread		1.743	1.735	1.726	1.716	1.594
	Abs change		-0.008	-0.017	-0.027	-0.149
	Rel change		-0.463	-0.992	-1.525	-8.522

3.5.3 Shorter data histories

The US mortgage market may be unique as many mortgages are securitized by GSEs, such as Fannie Mae or Freddie Mac. This provides public data histories for empirical research. However, lenders may not have such a history, and the results may not be well-calibrated. We extract the samples where the loan age is a maximum of ten years and present the results in Panel B of Table 3.10.[80] We find consistent results for shorter histories.

3.5.4 Sample with recourse and nonrecourse mortgages

In the main analysis, we only use recourse mortgages to highlight the importance of liquidity in driving the default risk. We provide the robustness test for the full sample in Panel C of Table 3.10. The full sample contains approximately 50 million observations. The model generates similar and consistent results.

3.6 Findings and implications

This paper analyzes personalized mortgage contracts that accommodate borrower specific dynamic incomes and risk levels over the lifetime of the loans. We find that AFRMs are most effective in reducing default risk, improving financial resilience, and enhancing the return ratio for lenders or their competitiveness in the mortgage market. IFRMs induce similar effects but they are not as compelling as AFRMs. These risk reductions lead to a reduction in capital

[80] We also conduct an analysis where loan age is shorter than seven years and the results are consistent.

costs, resulting in higher lender returns or consumers benefitting from a lower credit spread. The findings are robust for several tests.

Both contracts change the timing of repayments and reduce borrower liquidity constraints (DTI) and increase leverage (LTV). While minimizing the probability of default, they may increase the loss given default to some degree. The overall impact is limited as the variation of DTI is greater than the variation of LTV, and the LGD is only relevant conditional on the occurrence of defaults.

There are, however, some limitations in the deployment of personalized contracts. IFRMs apply income growth rates over loan lifetime (legal 30 years, actual seven years). Current socioeconomic changes, including work from home, climate change, and inflation, may alter future growth rates. One option would be to build forecast models that can better support growth rate calculations. This aspect supports the application of AFRMs as the age profile is very robust over time and more independent from economic cycles as human lifecycles persist.

DPFRMs and DFRMs are comparatively easier to implement, as they involve a straightforward financial adjustment for several payment periods. In addition, DPFRMs and DFRMs only need to be applied to a subset of total loans based on delinquent status. Combined with a robust data management approach, this product can be used selectively to target the loans most likely to face default. A key point to consider would be when to trigger these two contract adaptations, as the immediate loss in cash flow can be restrictive on lender operations and would need coordination with regulatory bodies to ensure continuous service. The application of loan deferrals may trigger loan loss provisions, necessitating a capital increase with additional costs. Some countries temporarily halted the provisioning process during COVID.

We view the proposed personalized IFRMs and AFRMs as compelling mortgage contracts for financial institutions. Its deployment into the general banking system will financially benefit borrowers and lenders. DPFRMs and DFRMs are beneficial as temporary payment adjustments that can alleviate the immediate risk of default and allow borrowers and lenders time to explore alternative solutions. In combination, they can allow a lender to provide a greater level of mortgage customizations up-front while maintaining a series of backstops according to changes in the local environment. For borrowers, all contracts are better aligned to their liquidity profiles. In addition, they may further enhance their liquidity through second-lien home equity loans (HELs), home equity lines of credit (HELOCs), or loans with negative amortization features.

Care should be taken during the implementation phase of the new contracts as the impact on consumer behaviour is unclear and subject to careful testing during the implementation phase. In particular, it remains unclear how consumers may use excess liquidity: they may increase risk elsewhere or housing markets may absorb greater purchase potential via higher house prices. We have developed a hybrid FRM contract where the borrower pays constant annuities as in existing FRM contracts until the peak risk year and increases payments similar to the AFRM thereafter.

For future work, other mortgage designs may be worth considering, including contracts that provide shared equity arrangements and enhance LTV or a combination of liquidity and equity-enhancing contract designs. Ultimately all contract designs need to be use-tested. Regulators may actively support lenders to try new contracts by making capital requirements more flexible to accommodate new contract designs and bring them to a similar level of provisioning and capital treatment as existing contract designs during trial periods.

Appendix 3.A: Variable description

Note: The data source of indicator variables, borrower characteristics, loan characteristics, contagion is from the Federal Housing Finance Agency. Unemployment rate, GDP and HPI growth are sourced from the FRED database provided by the St. Louis Federal Reserve Bank. Income growth at the zip code level is collected from the IRS. Contagion and age growth factors are self-calculated.

Variable	**Description**
Default	Dummy variable is one if a mortgage is foreclosed and zero otherwise
Payoff	Dummy variable is one if a mortgage is paid off and zero otherwise
Indicator	Categorical variable is one if a mortgage defaults, two if it is paid off and zero otherwise
DTI	Current Debt-to-Income ratio which is the ratio between a borrower's periodic payment and the total income adjusted by the 3-digit zip code's income growth
LTV	Current Loan-to-Value ratio which is the ratio between the scheduled loan balance and current property value adjusted by the 3-digit zip code's HPI index
FICO	Borrower's credit score provided by Fair Isaac & Company
Orig_Loansize	Natural logarithm of original loan balance
Mgt insurance	Dummy variable is one if the mortgage insurance is requested and zero otherwise
Investment	Dummy variable is one if the underlying property is used for investment purpose, and zero otherwise (residence purpose)
Prepayment_penalty	Dummy variable is one if a mortgage has prepayment penalty and zero otherwise
Multi_borr	Dummy variable is one if a mortgage has more than one borrower and zero otherwise
TPO	Dummy variable is one if a mortgage is originated through a third-party originator and zero otherwise
NotSF	Dummy variable is one if the underlying property is not a single-family home and zero otherwise
Interest_rate	Interest rate on mortgage
MSA	Dummy variable is one if the underlying property is located in an MSA and zero otherwise
Age	Loan age: Time between current time and origination time
Age5	Spline variable is zero if loan age is up to 5 and Age minus 5 if loan age is longer than 5
Age7	Spline variable is zero if loan age is up to 7 and Age minus 7 if loan age is longer than 7
Age9	Spline variable is zero if loan age is up to 9 and Age minus 9 if loan age is longer than 9
Age11	Spline variable is zero if loan age is up to 11 and Age minus 11 if loan age is longer than 11
Age13	Spline variable is zero if loan age is up to 13 and Age minus 13 if loan age is longer than 13
HPI_{-1}	One-period lagged HPI
GDP $Growth_{-1}$	One-period lagged GDP growth
$Contagion_{-1}$	One-period lagged default rate at the zip code level
g_s	Geometric average of income growth at the state level
k_1	The age growth used for the period from the origination to the peak (year 9)
k_2	The age growth used for the period after the peak

Appendix 3.B: Generalization of scheduled payments for AFRMs with j growing annuities (j>1)

Assuming that the first payment is $1, the present value of each growth rate regime is as follows:

The first growth rate regime lasts for d_1 periods, from the first period to period m_1. The PV is:

$$PV_1 = \frac{1}{i - k_1} - \frac{1}{i - k_1}\left(\frac{1 + k_1}{1 + i}\right)^{m_1}$$

The second growth rate regime lasts for d_2 periods from period m_1+1 to period m_2. The PV is:

$$PV_2 = \frac{1}{i - k_2} - \frac{1}{i - k_2}\left(\frac{1 + k_2}{1 + i}\right)^{m_2 - m_1}$$

…

The (j-1)th growth rate regime lasts for d_{j-1} periods, starting from period m_{j-2}+1 to period m_{j-1}. The PV is:

$$PV_{j-1} = \frac{1}{i - k_{j-1}} - \frac{1}{i - k_{j-1}}\left(\frac{1 + k_{j-1}}{1 + i}\right)^{m_{j-1} - m_{j-2}}$$

The jth growth rate regime lasts for d_j periods, starting from period m_{j-1} to the end of maturity (n) is:

$$PV_j = \frac{1}{i - k_j} - \frac{1}{i - k_j}\left(\frac{1 + k_j}{1 + i}\right)^{n - m_j}$$

The total PV (i.e., original loan balance) is calculated as the sum of these above cash flows after we discount it to the present time.

If there is only one growth rate over the maturity and the first cash flow of this regime is AA, the PV equals to:

$$PV = AA * PV_1$$

If there are two growth rates over the maturity and the first cash flow of the second regime is $AA(1+k_1)^{d_1-1}(1+k_2)$, the PV equals to:

$$PV = AA * PV_1 + \frac{AA * PV_2(1+k_1)^{d_1-1}(1+k_2)}{(1+i)^{m_1}}$$

If there are three growth rates over the maturity and the first cash flow of the third regime is $AA(1+k_1)^{d_1-1}(1+k_2)^{d_2}(1+k_3)$, the PV equals to:

$$PV = AA * PV_1 + \frac{AA * PV_2(1+k_1)^{d_1-1}(1+k_2)}{(1+i)^{m_1}} + \frac{AA * PV_3(1+k_1)^{d_1-1}(1+k_2)^{d_2}(1+k_3)}{(1+i)^{m_2}}$$

We generalize the PV equation if there are j growth rates over the maturity (j>1) as follows:

$$B = PV = AA * PV_1 + AA(1+k_1)^{d_1-1} \sum_{r=2}^{j} \left\{ \left[PV_r(1+k_r) \prod_{\substack{l=2 \\ r>2}}^{r-1} (1+k_l)^{d_l} \right] / (1+i)^{m_{r-1}} \right\}$$

The first payment (AA) therefore equals to:

$$AA = \frac{B}{PV_1 + (1+k_1)^{d_1-1} \sum_{r=2}^{j} \frac{PV_r(1+k_r) \prod_{\substack{l=2 \\ r>2}}^{r-1} (1+k_l)^{d_l}}{(1+i)^{m_{r-1}}}}$$

The scheduled payment (SPA) is:

$$SPA_t = \begin{cases} AA(1+k_1)^{t-1} & \text{if } t \le m_1 \\ AA(1+k_1)^{d_1-1}(1+k_2)^{t-m_1} & \text{if } m_1 < t \le m_2 \\ \quad \dots & \\ AA(1+k_1)^{d_1-1}(1+k_{j-1})^{t-m_{j-2}} \prod_{l=2}^{j-2}(1+k_l)^{d_l} & \text{if } m_{j-2} < t \le m_{j-1} \\ AA(1+k_1)^{d_1-1}(1+k_j)^{t-m_{j-1}} \prod_{l=2}^{j-1}(1+k_l)^{d_l} & \text{if } m_{j-1} < t \le n \end{cases}$$

Appendix 3.C: Analysis for Well Fargo and Countrywide Home loans

Note: This table reports the analysis for Wells Fargo, a bank representative, and those originated by Countrywide Home Loans, a nonbank representative, including the absolute change and relative change in Mean PD, systematic risk, regulatory capital, ROC, and new spread between FRMs and other contracts. Mean PD is the average PD estimated from the multinomial logit regression specified in Eq. (3.27). Systematic risk is the difference between Peak PD (maximum PD) and Mean PD. Regulatory capital is calculated using Basel regulation. ROC is the ratio between credit spread and regulatory capital. The credit spread equals to interest rate minus risk-free rate (the 30-year Treasury rate). New spread equals to ROC of FRMs multiplying regulatory capital. All values are expressed as percentages.

	Well Fargo					Countrywide Home Loan				
	FRM	DPFRM	DFRM	IFRM	AFRM	FRM	DPFRM	DFRM	IFRM	AFRM
Mean PD	0.398	0.397	0.394	0.384	0.344	1.007	1.004	0.994	0.976	0.858
Abs change		-0.001	-0.004	-0.014	-0.054		-0.003	-0.013	-0.031	-0.149
Rel change		-0.251	-1.005	-3.518	-13.568		-0.298	-1.291	-3.078	-14.796
Systematic risk	0.906	0.924	0.987	0.888	0.734	2.424	2.482	2.679	2.413	1.865
Abs change		0.018	0.081	-0.018	-0.172		0.058	0.255	-0.011	-0.559
Rel change		1.987	8.940	-1.987	-18.985		2.393	10.520	-0.454	-23.061
Regulatory capital	3.349	3.342	3.323	3.264	3.018	6.358	6.344	6.302	6.227	5.713
Abs change		-0.007	-0.026	-0.085	-0.331		-0.014	-0.056	-0.131	-0.645
Rel change		-0.209	-0.776	-2.538	-9.884		-0.220	-0.881	-2.060	-10.145
ROC	51.136	51.244	51.532	52.461	56.745	31.710	31.777	31.992	32.376	35.288
Abs change		0.108	0.396	1.325	5.609		0.067	0.282	0.666	3.578
Rel change		0.211	0.774	2.591	10.969		0.211	0.889	2.100	11.284
New spread	1.712	1.709	1.699	1.669	1.543	2.016	2.012	1.998	1.975	1.812
Abs change		-0.003	-0.013	-0.043	-0.169		-0.004	-0.018	-0.041	-0.204
Rel change		-0.199	-0.767	-2.529	-9.875		-0.217	-0.878	-2.057	-10.142

Appendix 3.D: Risk class formation

Note: This table presents the formation of risk classes, including number of observations, number of default (foreclosure) events, default (foreclosure) rate, and mean PD from the through-to-cycle model which only includes time-invariant variables. The foreclosure rate and mean PD are expressed in percentages

	No of obs.	**No of default events**	**Default rate**	**Mean PD**
Lowest risk	24,187,481	11,310	0.047	0.057
2	2,947,863	11,311	0.384	0.379
3	1,767,765	11,311	0.640	0.596
4	1,219,479	11,311	0.928	0.836
5	914,750	11,311	1.237	1.122
6	682,165	11,311	1.658	1.480
7	541,145	11,311	2.090	1.953
8	411,328	11,311	2.750	2.638
9	309,584	11,311	3.654	3.782
Highest risk	196,861	11,311	5.746	7.065

Chapter 4 : Unravelling the dynamic effects of conforming loan limits on house prices

4.1 Introduction

CLL is an important tool for regulating the mortgage market, enhancing housing affordability and access to credit for homebuyers. By setting limits on loan amounts, the CLL helps ensure that mortgage financing is available to a wide range of borrowers, including those in high-cost areas. It also provides a framework for lenders to assess risk and make lending decisions. Mortgages that fall within the CLL limits typically have more favourable terms and interest rates compared to non-conforming loans.

The FHFA adopted new guidance supposed to reflect the changes in the national house price index (HPI) in the CLL, which is the securitization limit for Government Sponsored Enterprises (GSEs) such as Fannie Mae and Freddie Mac in 2008. Under the new guidance, the base CLL remained unchanged until 2016 despite the declining HPI. Since 2017, the CLL has increased annually and reached the highest level ever in December 2022 due to the constant growth of house prices. In short, the CLL growth should reflect the housing market conditions but remains positive, which may indicate a certain level of regulatory bias. While this policy aims to support homebuyers, there is a strong debate as to whether this manipulates (here artificially increases) house prices and creates price distortions in the housing market and inequalities in the economy.

Thanks to the updated data, we notice two different regimes in adjusting the CLL over the periods from 2010 to 2021. CLL growth diverges from HPI growth prior to 2017 but perfectly aligns with HPI growth afterward. Whether these CLL regimes have different effects on HPI has yet to be uncovered in the literature. In addition, little is known about the response heterogeneity to regulatory intervention from distinctive lenders and borrowers in the market and how their financial constraints contribute to shaping house prices under the CLL adjustments. Our paper addresses these issues and aims to provide a more comprehensive understanding of how mortgage-related regulatory variations affect the housing markets and the moderating roles of financial constraints.

There is potentially an endogeneity problem when examining the effect of CLL changes on house prices, as those changes are not randomly assigned but rather a function of the lagged HPI growth. We employ a two-stage strategy to circumvent this problem. In the first stage, we purge the endogenous variations from the CLLs by regressing CLL growth on HPI growth and obtaining the residual. To ensure the residual, later named regulatory bias, truly reflects exogenous variations in the CLLs, we incorporate county-level controls representing demographic characteristics, housing and economic conditions and county fixed effects controlling for unobservable factors. In the second stage, we regress the house prices on residual to obtain the effect of relative CLL changes on house prices. The analyses related to differential regimes and the moderating roles of financial constraints also rely on the estimated residual.

There are several areas in which our paper improves upon the current literature. First, we study CLL changes for two regimes. We uncover that the positive effect of regulatory bias remains and becomes more substantial for the pre-2017 period but vanishes during recent years. This effect is explained through the credit supply channel. Our research suggests that the housing market will not become distorted or experience undue manipulation if CLL and house price growth are aligned. This is important as an extrapolation of prior studies would lead to the false alarm that CLL growth was causal to the recent house price increase.

Second, we are first to analyze the moderating roles of lender and borrower constraints on the effect of relative CLL changes on house prices. The effect becomes more pronounced for bank-dominated counties, borrowers in non-recourse states, and those less financially constrained. Bank lenders are found to have fewer constraints in accessing different funding sources and be keen on originating larger loans.[81] They are, therefore, more sensitive to CLL increases as they can make more larger loans and enlarge their customer base. Consequently, banks tend to play a more critical role in driving house prices. For borrowers, we find that non-

[81] Another consideration is that banks prefer to originate jumbo loans over conforming loans due to regulatory burdens, see D'Acunto and Rossi (2021) and Haughwout et al. (2022).

recourse borrowers drive the effect of regulatory bias on house prices more than recourse borrowers. It is more flexible for non-recourse borrowers to get extra credit as their personal liabilities are limited in the event of default. In contrast, recourse borrowers may be more reluctant to obtain more credit when a higher loan limit is set due to the fear of legal action against their defaults and the increasing repayment burden. Less financially constrained borrowers can also take advantage of the increased CLLs as they will have better equity and liquidity to meet the requirements of a larger loan.

Last, we contribute to the method of dealing with endogeneity concerns when house prices and CLLs are linked by design. Earlier studies may either rely on outdated assumptions or employ a smaller sample size of adjacent areas to validate the exogenous nature of CLL changes, which may lead to biased and less accurate estimates. We address this endogeneity by purging out the endogenous variations in CLLs through regressing CLL growth on lagged house price growth and multiple county-level controls for observed and unobserved factors before examining the effect of relative CLL growth on house prices. This approach is novel and could be applicable to similar endogenous interventions.

Our findings carry practical implications for regulators. Policymakers should be aware of the unexpected effect of their CLL-related interventions in driving up house prices. Adjustments should firmly align with historical house pricing trends. Regulators should also consider the heterogeneity of market participants when making policies, as their financial constraints play an important role in driving any effects on house prices.

The remainder of this chapter is organized as follows: Section 4.2 discusses related literature; Section 4.3 provides information on the history of CLL; Section 4.4 states the data sources and describes the data; Section 4.5 reports and discusses the empirical results; Section 4.6 presents the results of the robustness test; and Section 4.7 concludes the paper, provides the policy implications, and suggests future work.

4.2 Related house price literature

4.2.1 The effect of credit supply on house prices

One of the main drivers of house prices is the credit supply expansion. The literature has found that the increased credit supply induced by easier credit access leads to housing bubbles. Credit supply growth has been linked to lower real interest rates (Taylor, 2013), lower down payments and higher approval rates (Khandani et al., 2013), the combined effect of relaxed credit constraints and lower housing transaction costs (Favilukis et al., 2017) and heterogeneous expectations of different agents in the market (Burnside et al., 2016; Favara & Song, 2014).

Credit supply growth usually results from exogenous shocks under policy interventions. Di Maggio and Kermani (2017) find that the exemption of national banks from local laws against predatory lending allows them to increase lending, leading to a rise in house prices. By examining the effect of introducing the Interstate Banking and Branching Efficiency Act in 1994, Favara and Imbs (2015) indicate that branching deregulation can explain the growth of credit supply and, subsequently, house price increases. A recent study by Berger et al. (2020) investigates the effect of the $20-billion stimulus program regarding a temporary tax incentive for first-time homebuyers. They confirm an increase in median house prices due to the program exposure. Quincy (2022) investigates the effect of income packages offered to veterans of World War I on house prices. The income shock allows recipients to buy houses more easily but causes a negative spillover effect on the neighborhoods. Monetary and fiscal policies can also positively impact credit supply (Iacoviello, 2005; Jiménez et al., 2012).

4.2.2 Loan funding through securitization

Mian and Sufi (2009) find that the main driver in the expansion of mortgage credit within various counties was due to an increase in the securitization of subprime mortgages. This securitization channel has played an essential role in the U.S. mortgage market, providing liquidity for mortgage lenders. A lack of securitization, implying a higher interest and prepayment risk for lenders, leads to a contraction in the credit supply (Calem et al., 2013; Fuster & Vickery, 2015; Loutskina & Strahan, 2009). Other empirical findings demonstrate the relationships of securitization and loan performances (Elul, 2016; Krainer & Laderman, 2014) or capital arbitrage (Ambrose et al., 2005).

Government-sponsored enterprises (GSEs) have set up the CLL, the maximum loan amount they agree to buy. In other words, the existence of the CLL is generally approximated as the availability of securitization or government guarantees. It could be argued that any increases in the CLL are supposed to induce the growth of credit supply, especially in the conforming section, which generates cheaper credit, simulates housing demand, and use prices.

CLL changes are endogenous to house prices as the CLL is practically adjusted by the one-year lagged growth of the national HPI. The study from Adelino et al. (2012) argues that CLL adjustment is only influenced by the national house price appreciation and hence estranged from local housing market conditions. Treating the annual change in CLL as an exogenous shock, they found a positive relationship between CLL and house value from 1998 to 2008, when a single conforming limit was uniformly imposed across 48 states. Adelino et al. (2012) analyze the effect of CLL-induced credit supply on house prices and find a greater link for areas with lower housing supply elasticity. Lilley and Rinaldi (2021) employ a sample of counties sharing state borders, and the data sample ranges from 2000 to 2017 and find that credit supply leads to house price increases.

Other research has analyzed the impact of CLL on other economic features, such as home ownership and loan origination standards. Grundl and Kim (2021) view the variations in the CLL as a proxy for government guarantees and find that government action could only marginally promote homeownership. Rajan et al. (2015) and Choi and Kim (2021) find that lenders tend to spend less time screening applications or only focus on hard information if the loan amount is below the conforming limit. Ouazad and Kahn (2022) indicate that lenders' perception of disaster risk is a critical factor driving bunching behavior at the CLL. Kaufman (2014) found that GSE-eligible loans could carry a lower interest rate by about 10 bps.

4.2.3 Lender and borrower constraints

Some research has looked at lender constraints in supplying credit which mainly focus on their access to funding. For example, Jiménez et al. (2012) look at bank capital and liquidity and indicate that a stronger bank balance sheet strengthens the induction of credit available through the changes in short-term interest rates and economic growth. Jiang (2023) finds that shadow banks tend to rely on their bank competitors in relation to funding. However, the existence of secondary market innovation (i.e., mortgage securitization) could allow them to be more independent and strengthen their competition in mortgage markets. Fuster et al. (2021) find that labor market frictions and operational bottlenecks reduce the elasticity of mortgage credit supply during the Covid-19 pandemic. However, technology-based lenders are less constrained by frictions and gain market shares in this period.

There is also literature on borrower constraints in obtaining credit. These constraints are mainly associated with borrower equity (i.e., usually proxied by loan-to-value ratio) and liquidity (i.e., usually proxied by debt-to-income ratio). Acolin et al. (2016) thoroughly review the relationship between borrower constraints and homeownership. Most studies point out the negative association that higher restriction leads to lower homeownership. Besides the financial conditions, the regulation could also contribute to borrower constraints. Ghent and Kudlyak (2011) show that recourse law reduces the probability of default, hence acting as a borrower disciplining constraint. In other words, borrowers exposed to recourse law are more constrained by getting additional credit due to the possibility of increasing default risk from onerous repayments. Bostic and Gabriel (2006) state that the effect of GSE home loan purchase on raising homeownership is limited for low-income borrowers and suggest alternative solutions for more affordable housing options for this underserved group.

4.2.4 Contribution

Our paper makes a number of first-in-kind contributions to this literature. First, we document a positive effect of CLL growth on house price growth in years before 2017 but not after that, including the recent increase in house prices. This is important as an extrapolation of prior studies would lead to the false alarm that CLL growth was causal to the recent house price increase. Second, we are first to analyze the moderating roles of lender and borrower constraints on the effect of relative CLL changes on house prices. Examining these two dimensions helps provide a comprehensive picture of how different lenders and borrowers react to the CLL adjustment and whether the heterogeneous responses exert distinct impacts on home values. This allows us to derive practical implications for policymakers. Third, we develop a novel methodology that better addresses endogeneity by regressing CLL growth on lagged house price growth and several county-level factors. By employing this approach, we are able to isolate the exogenous variations in CLLs, enabling a more rigorous analysis of the causal relationship with house prices.

4.3 History of the conforming loan limit (CLL)

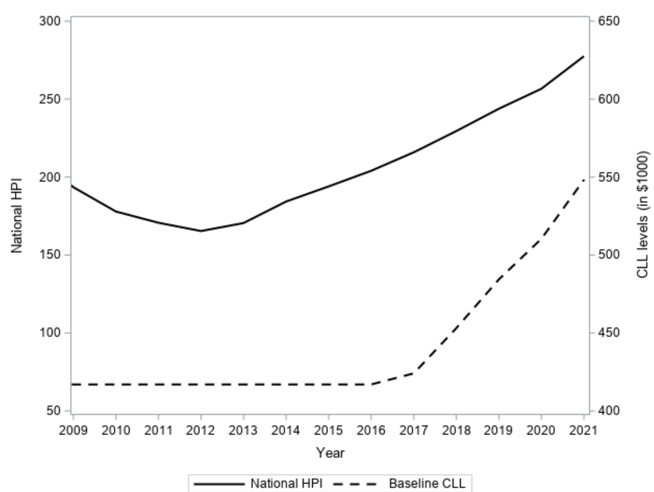
The conforming loan limit is the absolute dollar cap on the size of a mortgage that GSEs including Fannie Mae and Freddie Mac will purchase or guarantee. Mortgages that meet the criteria for backing by the two GSEs are known as conforming loans, while those above the limit are known as jumbo loans. An originate-to-distribute model (i.e., securitization) has been one of the growing trends in the mortgage market in the post-crisis period. According to the report from FDIC (2019), nonbanks likely sold up to 97 percent of their 1-4 family loan portfolios while banks sold approximately 50 percent. The majority of their securitization volume is through the GSEs. Meeting the CLLs which is determined by FHFA is the crucial factor for lenders aiming for government-backed securitization.

The loan limit increases reflect the year-over-year percentage change in the FHFA HPI between the third quarter of the previous year and the third quarter of the current year. For example, the percentage change in HPI between October 2021 and October 2022 is 12.2 percent, which implies that the increase in baseline CLL in 2023 of 12.2 percent relative to the baseline level in 2022. However, the baseline loan limit value remains flat when the national average home price is decreasing. When the home values come back up, CLL remains unchanged until the prior declines are fully made up. The FHFA aims to prevent the CLL from going down and will intervene if there are significant decreases in housing prices over multiple years.

In May 2007, the Housing and Economic Recovery Act (HERA) was passed, which increased the CLL in high-cost areas. Specifically, properties that are in certain metro or micropolitan areas have a temporary loan limit of up to 1.25x the median house price. Regardless of the area median home price, the loan limit could not exceed 175 percent of the baseline limit. From July 2007 to December 2008, the increased limit was applied and remained unchanged for mortgages originated in 2009 and 2010 despite a decline in HPI.

Between 2009 and 2014, there were no significant changes to the CLL despite a growing decline in house prices. The maximum CLL for mortgages originated in 2011 remained unchanged, and only one county in Connecticut had a slight increase. The CLL was linked to the maximum limit of either the Economic Stimulus Act (ESA) or HERA, with the ESA being higher than HERA in many cases. Although the FHFA looked at alternative methods to calculate the CLL using new models, these resulted in large declines, which were prohibited by the current regulations. If home values decline, the loan limits remain the same as the previous year until the house price index increases back to the level before it drops. Therefore, the baseline limit remained unchanged at $417,000 from 2006 until 2016.

Figure 4.1 visualizes the levels and cumulative growths of national HPI and baseline CLL over time.



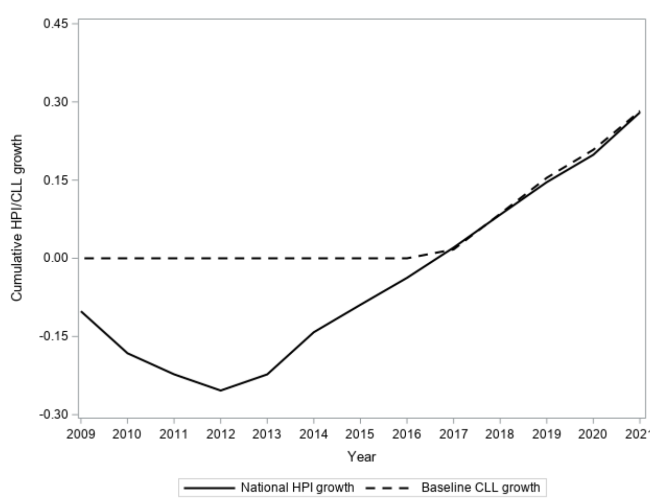


Figure 4.1: National HPI and Baseline CLL over time

Note: These figures plot the levels and growth of national HPI (solid line) and baseline CLL (dashed line) over the period 2009 to 2021. The upper figure plots the levels of HPI and CLL, while the lower figure plots the growth of HPI and CLL. The baseline CLL growth is adjusted by the growth of national HPI growth in the previous year. At year t, we plot the HPI level/growth at year t-1 and the CLL level/growth at year t.

Since 2017, the baseline limit has increased every year in response to rising home prices. In particular, the baseline CLL was increased to $424,100 from $417,000 in 2017 after 10 years of remaining unchanged. The limit continued to rise each year, reaching $548,250 in 2021. In 2022, the FHFA announced a record 18 percent increase in the loan limit, responding to rising home prices. The cumulative growth provides us with a better picture of the alignment between CLL and national HPI. We observe a better alignment between CLL growth and HPI growth since 2017 but large divergences during the earlier periods.

The CLL levels can vary across counties. Most counties apply the baseline limit, while around 100 high-cost counties have a higher limit due to higher house prices compared to the national level. The same level of high-cost CLL will be applied for all counties in the same core-based statistical area (CBSA). FHFA calculates these CLL values are set at 115 percent of the median home value for the highest-cost component county in the local area but cannot exceed 150 percent of the baseline limit. Figure 4.2 visualizes the average cumulative national HPI and high-cost CLL growth over time.

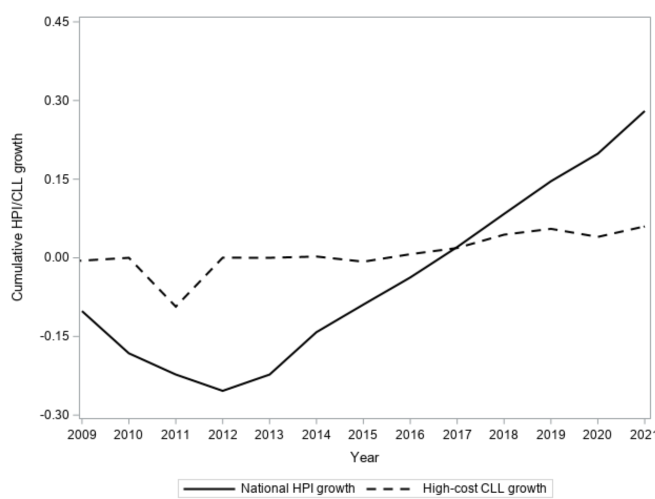


Figure 4.2: National HPI growth and High-cost CLL growth

Note: This figure plots the cumulative national HPI growth (solid line) and the high-cost CLL growth (dashed line) from 2009 to 2020. We take the average cumulative high-cost CLL growth for each year. Similar to Figure 4.1, at year t, we plot the HPI growth at year t-1 and the CLL growth at year t.

It can be seen from the figure that the two growth rates are completely misaligned. High-cost CLL growth is higher than HPI growth before 2017 but lower after 2017. As high-cost CLL levels are derived from the baseline CLL, these misalignments could indicate the existence of regulatory bias. This was proven in 2008 when the regulator adjusted the CLL levels for some counties (FHFA, 2008).[82]

4.4 Data description

4.4.1 Data sources and pre-processing

We use the Home Mortgage Disclosure Act (HMDA) data from the Consumer Financial Protection Bureau as the main database to address the research questions. HMDA data provide information on loan applications and approvals in the United States. The data reports the application outcome, loan and borrower characteristics, property location, census-tract-related characteristics, and lender identity information. The application outcome indicates if lenders approve and originate the loans or reject the application along with the reason. Loan information includes property location with tract and county codes, loan type (conventional or nonconventional), property type (single-family or multi-family), loan purpose (purchase or refinance), loan amount, types of the purchaser, and occupation type (residence or investment). Borrower information provides the ethnicity, race, gender, income, and similar information for co-applicants if available. The census-tract-level information provides the population, percentage of minority groups, median family income, and housing characteristics.

We collect the HMDA data for the period from 2010 to 2021 with more than 200 million

[82] CLL levels are also higher for properties with multiple units. The variations in CLL levels for different types of properties are parallel, indicating no evidence of regulatory bias. To that end, we only retain the loans supporting single-family homes in our sample.

observations, covering approximately 90 percent of loan applications in the U.S.[83] We apply several filters to ensure data homogeneity: First, we remove loans with missing values on the loan amount as this information is required for our credit supply proxy. Second, we keep loans supporting single-family houses as the growth of CLL levels for multiple-family units is similar but limited by lower observation counts. Third, we keep loans originated by the top 300 lenders regarding the number of applications to categorize lenders into banks and non-banks.[84] Fourth, we remove loans with home improvement purposes as these loans are generally small in size and are not directly related to house purchases. The total data sample consisted of more than 74 million approved applications in roughly 197 million submitted applications during the research period.

The data on CLLs at the county level is collected from the FHFA. These limits are categorized into baseline limits and high-cost area limits. Areas are defined as high-cost counties if 115 percent of their median home value exceeds the baseline limit. Regarding the demographic and macroeconomic county-level data, we obtain housing stock, median household income, and population using the American Community Service 5-year estimates from the Census Bureau and the real GDP level from the Bureau of Economic Analysis. All data are collected for the period from 2010 to 2021.

Lastly, we obtain the data on house prices. To align with the policy guidelines, we use the seasonal-adjusted and quarterly expanded-data US-level index series from the FHFA. This is used to construct the proxy of regulatory bias in Section 5.1. We retain the observations of the third quarter only as the baseline CLL is adjusted by the percentage change between the two consecutive third quarters. We consider two proxies for county-level house prices: ZHVI All homes from Zillow and the annual county-level HPI from the FHFA. The Zillow Home Value Index measures the monthly changes in the property level by capturing both the level and

[83] We collect data from 2010 to match with the county-level macroeconomic variables. Most county-level data collected from the American Community Service data is only available from 2010.

[84] There are approximately 6000 lenders in the full sample, and it would be time-consuming to classify each lender. In fact, the top 300 lenders occupy roughly 80% of market share.

appreciation of home values across a wide variety of geographies and housing types. Meanwhile, the FHFA House Price Index is a measure of the movement of single-family house prices. It measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. In summary, the Zillow index covers a broader range of housing transactions, including homes with and without government-back mortgages and the FHFA index focuses on properties with mortgages backed by GSEs. We use ZHVI All in the main analysis as it is smooth, seasonally adjusted, and more reflective of the general housing economy and FHFA HPI in a robustness check.

We transform the data to the county-year level to fit the regression framework. The data on CLL, house prices, and county-level macroeconomic variables are at the county-year level, so we only perform the transformation for the HMDA data. We aggregate the total amount of lending, the total amount of bank and non-bank lending, and the number of bank lenders for each county-year. Similarly, we count the number of joint applications, the number of conventional loans, the number of refinancing loans, the number of loans for residence purposes, the number of securitized loans, and the number of loans with female/Latino/Black applicants. These counts are used to construct the loan- and borrower-specific control variables.

4.4.2 Descriptive statistics

Table 4.1 describes data used in our analysis, including the CLL, national HPI, county-level house prices, county-aggregated HMDA data, and county-level macroeconomic variables over the 2010-2021 period. The data is processed at the county-year level.

Table 4.1: HMDA data description

Note: This table presents the descriptive statistics of county-aggregated HMDA data and county-level macroeconomic variables. Absolute values, except indexes, are enclosed with the measurement units. All log returns and ratios are displayed in percentages.

	Mean	Std	Min	Max	No of obs.
Conforming loan limit					
CLL ($)	455,073	62,125	417,000	822,375	38,491
Baseline CLL ($)	445,181	43,453	417,000	548,250	36,173

High-cost CLL ($)	596,833	102,833	417,500	822,375	2,632
Log return CLL	2.172	3.533	-41	46	38,491
Log return baseline CLL	2.280	3.123	0	7	36,173
Log return high-cost CLL	1.285	5.747	-41	46	2,632
National HPI					
National HPI	220	50	165	329	12
Log return national HPI	5.131	5.382	-4	17	12
Credit supply					
Total loan amount (in m$)	486	2,487	0	131,666	38,497
Log return total loan amount	4.988	39.328	-374	444	38,485
No of originations	1,925	7,243	1	269,060	38,497
Log return no of originations	2.520	32.219	-291	262	38,485
No of approved applications	2,204	8,086	1	333,150	38,497
Log return no of approved apps	5.597	32.104	-256	235	38,485
County-level house prices					
Zillow home values ($)	150,862	103,474	14,878	2,291,003	32,202
Log return Zillow home values	5.315	6.790	-40	77	31,163
FHFA HPI	280	185	64	2,117	33,097
Log return FHFA HPI	2.468	5.381	-48	44	33,025
Loan and borrower characteristics					
Mean loan amount ($)	155,691	71,732	11,000	1,649,000	38,497
Mean borrower income ($)	86,381	40,861	14,000	2,221,742	38,485
% bank lenders	15.667	18.624	0	100	38,497
% bank loan amount share	46.746	21.269	0	100	38,497
% securitization	72.853	14.134	0	100	38,497
% conventional loans	65.128	14.707	0	100	38,497
% joint applications	46.668	10.983	0	100	38,497
% refinancing loans	51.532	16.415	0	100	38,497
% residence loans	92.738	9.090	0	100	38,497
% female applicants	25.809	8.332	0	100	38,497
% Latino applicants	6.892	16.720	0	100	38,497
% Black applicants	4.420	8.432	0	100	38,497
County-level characteristics					
Log real GDP	13.913	1.580	9.210	20.383	36,927
Log median household income	10.746	0.299	9.259	11.963	38,481
Log housing stock	9.699	1.342	4.625	15.154	38,483
Log population	10.285	1.451	4.043	16.129	38,483

CLL is lower for baseline counties and higher for high-cost counties. We obtain an annual increase in CLL of 2.3 percent for baseline counties and 1.3 percent for high-cost counties. The annual growth rate of CLL in high-cost counties exhibits more fluctuations compared to those in baseline counties. In high-cost counties, the annual growth ranges from -41 percent to 46 percent, while in the baseline counties, it varies between 0 to 7 percent. This large variance for high-cost counties is due to some scenarios where a county may change from high-cost to baseline or vice versa. This demonstrates the heterogenous growth in the CLL across different counties and may imply a certain level of regulatory bias in adjusting CLL levels. During the same period, we obtain an increase of 5.1 percent in the US-level HPI with a minimum growth of -4 percent and a maximum of 17 percent.

Regarding the credit supply at the county level, the average total loan amount is 486 million dollars per county and year, the average number of originations is around 1,900 loans, and the average number of approved loans is 2,200. We witness an increase of 5 percent in the total loan amount, 2.5 percent in the number of originations, and 5.6 percent in the number of approved applications. These numbers indicate an expansion in the credit supply.

For the county-level house prices, the Zillow county-level home values have increased by an average of 5.3 percent annually, and the average growth in price changes reflected in the FHFA HPI is recorded at 2.5 percent annually over the 11 years.[85] We notice wide ranges of these variations across counties: the annual growth of Zillow home values varies from -40 percent to 77 percent, and the growth in FHFA HPI varies from -48 percent to 44 percent. These variations could be either induced by local housing and economic conditions or influenced by government policies.

In terms of loan and borrower characteristics, the mean borrower income is around \$86,000 per annum, and the average loan amount is approximately \$156,000. Only 15 percent of lenders are banks, and their average market share is 46 percent. This share has dropped from around 70 percent in 2007 to 27 percent in 2021. The average securitization rate is 73 percent, indicating a strong originate-and-sell trend in the mortgage industry. Most loans are conventional and support residency, and there are no significant differences in joint applications and loan purposes. The proportions of loans originated for minority groups such as Latino or

[85] Note that this Zillow home value series reflects the growth of typical values for homes in the 35th to 65th percentile range (i.e., mid-tier). The county-level average log return of Zillow home values is 4.33% for the top tier (from 65th to 95th percentile range) and 7.53% the bottom tier (from 5th to 35th percentile range). Since these top-tier and bottom-tier series are not smoothed and seasonally adjusted yet, we employ the mid-tier series in our analysis. In addition, the mid-tier series could broadly reflect the growths of local housing markets.

Black applicants are only 6.8 percent and 4.4 percent, respectively, which are very small compared to their counterparts.

Finally, to capture the fundamental conditions of each county and their potential effects on house prices, we incorporate county-level macroeconomic variables. We consider housing stock as an indicator of housing supply, the real GDP as a measure of economic conditions, the median household income and population to construct proxies for demographic conditions. All variable ranges indicate a significant heterogeneity across counties and time.

4.5 Impact of regulatory bias on local home values

4.5.1 Measuring CLL-related regulatory bias

The simple regression of local home values on CLL may be biased because CLL is endogenous and driven by the previous-year national HPI growth. In other words, any significant relationship from this regression may be spurious due to the strong correlations of CLL and local home values with national HPI growth. Therefore, we carefully separate the endogenous and exogenous sources driving the CLL variations.

One solution suggested in the literature is to assemble a sample of areas sharing the border. For example, Grundl and Kim (2021) choose pairs of zip codes belonging to two adjacent counties, which expose the different changes in CLLs. The main assumption behind these choices is that adjacent zip codes/counties have a similar economic environment and are affected by the same factors. In addition, there is a need to control the variation across county pairs to estimate the causal effect of CLL on house prices accurately.

The border county sample may not completely account for all sources of endogeneity as there might be other time-varying factors that affect house prices and are correlated with CLL variations. We, therefore, suggest a method by which we first estimate the exogenous variations in CLL and employ it to examine the impact on local home values. The variations in CLL may be influenced by endogenous factors such as local housing, economic conditions, and regulatory decisions. By estimating the exogenous variations in CLL, we can better understand the level of regulatory bias.

According to the FHFA's guidelines on calculating the CLL, the baseline CLL is the function of the national HPI growth. The high-cost CLL is additionally exposed to local housing and economic conditions. We regress the CLL on lagged national HPI level and various county-level variables such as real GDP, lagged population, housing stock, and median household income. We take the log return (difference in logs) of all variables between the log of this year and log of the previous year.[86] We demean all county-level variables to control county-fixed effects.[87] For the baseline model, we follow the FHFA's rule by regressing the log return of CLL on the lagged log return of national HPI. The regression is described as follows:

$$\mathrm{CLL}_{\mathrm{B,c,t}} = \alpha_{\mathrm{B}} + \beta_{\mathrm{B}}\mathrm{HPI}_{\mathrm{t-1}} + \theta_{\mathrm{B,c}} + \varepsilon_{\mathrm{B,c,t}} \tag{4.1}$$

where the dependent variable is the log return of CLL, and the main independent variable is the one-year lagged log return of US-level HPI. County fixed effects are incorporated through the inclusion of demeaned county-level variables. Subscript B refers to the baseline model. Subscript c is an index for the county, and subscript t is an index for the year.

We further control local housing, economic and demographic conditions by including county-level macroeconomic variables ($C_{c,t}$) in the samples. The national HPI growth induces the adjustment of the baseline CLL. Local factors drive the high-cost CLL. Note that all variables are transformed into log-return forms. The integrated regression specification is adjusted as follows:

$$\mathrm{CLL}_{\mathrm{I,c,t}} = \alpha_{\mathrm{I}} + \beta_{\mathrm{I}}\mathrm{HPI}_{\mathrm{t-1}} + \gamma_{\mathrm{I}}\mathrm{C}_{\mathrm{c,t}} + \theta_{\mathrm{I,c}} + \varepsilon_{\mathrm{I,c,t}} \tag{4.2}$$

where subscript I refers to the integrated model, subscript c is an index for the county and subscript t is an index for the year. The residual from the integrated model captures the time-varying and fixed effects across different counties.

[86] Returns indicate relative changes. Log return CLL refers to the first difference in the log of CLL, which is equal to the log of the current CLL minus the log of the previous year's CLL. Similarly, the log return national HPI refers to the first difference in the log of national HPI.

[87] See Petrova and Westerlund (2020)

This method allows us to isolate any endogenous effects of the national HPI growth, observable and unobservable county-level factors on changes in CLL. As a result, the residual term $\varepsilon_{I,c,t}$ can capture the exogenous shocks to CLL, which is the relative CLL change or regulatory bias. We then use this residual to examine the impact of regulatory bias on local home values. This level of intervention is at log-change, county-specific, and can display the time-varying county component. Table 4.2 presents the regressions to estimate the regulatory bias.

The CLL variations in Model (1) are only exposed to the nationwide time-varying shocks, while we add the county-level time-varying shocks and fixed effects in Model (2). As expected, we observe the positive coefficients on the lagged US-level HPI in both models. Although the CLL adjustment is theoretically based on the national HPI of the previous year, controlling for the time-varying county-level effects is necessary and rational. We argue that the residual from the integrated model could reflect the exogenous variations in CLLs after isolating potential housing and economic conditions at both nationwide and local levels. We name the residual series as regulatory bias.

Table 4.2: Estimating regulatory bias

Note: This table presents the regression results of CLL on one-year lagged national HPI and other county-level controls. The residual from the regression is used as the proxy of the regulatory bias. Model (1) specified in Eq. (4.1) does not include county-level controls, Model (2) specified in Eq. (4.2) includes the county-level controls. We use the residual from Model (2) as the proxy of regulatory bias. The bottom panel presents the descriptive statistics of residuals. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Lagged log return of US-level HPI	
	(1) Baseline	**(2) Integrated**
Panel A: Model estimates		
US HPI$_{-1}$	0.322*** (0.003)	0.328*** (0.003)
GDP$_{-1}$		0.005*** (0.002)
Median household income		0.037*** (0.002)
Housing stock		0.058*** (0.004)
Population growth$_{-1}$		0.018 (0.016)
Intercept	-0.007*** (0)	-0.007*** (0)
County fixed effects	Yes	Yes
Adjusted R-square (%)	20.55	23.42

No of obs.	38,790	37,033
Panel B: Regulatory bias (Residual) description		
Mean	0.000	0.000
Std	0.031	0.029
Min	-0.430	-0.429
Max	0.403	0.401

The lower panel of Table 4.2 describes the residual series obtained from each model. The more accurate the models are, the lower the residual's standard deviation and the higher the adjusted R-squared. In addition, the value ranges between min and max are smaller. Model (2) proves to be a more accurate identification; hence we employ the residuals from Model (2) in the main analysis.

4.5.2 The effect of regulatory bias on house prices: Preliminary results

4.5.2.1 The direct impact of regulatory bias on house prices

We treat the level of regulatory bias as exogenous to local housing demand as it is obtained after controlling for the endogenous fluctuations of national HPI and county-level factors. We run the regression of house prices on the regulatory bias using the following identification:

$$\text{House\_price}_{c,t} = \alpha_{RF} + \beta \text{Reg\_bias}_{c,t} + \delta L_{c,t} + \tau_t + \theta_c + \varepsilon_{c,t} \qquad (4.3)$$

where the dependent variables are the log return of county-level Zillow home values, the primary independent variable is the regulatory bias, calculated as the residual from Model (2) in Table 4.2, $L_{c,t}$ represents the aggregated county-level loan and borrower characteristics[88], τ_t represents year fixed effects, θ_c represents county fixed effects. Subscript c is an index for the

[88] The loan and borrower characteristics include percentage of bank lenders, percentage of securitization, percentage of joint applications, percentage of residence properties, percentage of refinance loans, percentage of conventional loans, percentage of female applicants, percentage of Latino applicants and percentage of Black applicants.

county and subscript t is an index for the year.

The home value data is released at the end of the year, and regulatory bias through changes in CLL is determined at the beginning of the year. It is, therefore, appropriate to include contemporary left-hand and right-hand-side variables in the analysis. We do not incorporate the county-level macroeconomic variables into this model as their effects are already captured in regulatory bias as the outcome of the first-stage estimation.[89] The β coefficient indicates the impact of regulatory bias on local home values. We present the estimation results in Table 4.3.

Table 4.3: Impact of regulatory bias on house prices (reduced form)

Note: This table presents the results from the regression of house prices on regulatory bias using the full sample. The regression unit is at the county level. The proxy of house prices is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Log return of Zillow home values			
Regulatory bias	0.644*** (0.017)	0.122*** (0.018)	0.109*** (0.022)	0.107*** (0.022)
County-level controls	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes
County fixed effects	No	No	Yes	Yes
Adjusted R-square (%)	4.93	13.80	47.83	48.68
No of obs.	28,623	28,623	28,623	28,623

In the first model, we capture the effect of regulatory bias on house prices without the incorporation of either county-level factors or fixed effects. In the second model, we add control variables. In the third model, we add year and county fixed effects. The last model is the most complete. Due to regulatory CLL floors (non-decrease policy), we expect the coefficient on the regulatory bias to be positive. This is confirmed by significant positive impact on regulatory

[89] We later provide the robustness test including the county-level macroeconomic variables and obtain the consistent results.

bias in all regressions. The results are robust after adding county-level loan and borrower factors, year, and county fixed effects. Model accuracies also improve when we control more variations. From the most complete regression, the estimation indicates that the percentage change in the growth of Zillow home values is 0.107 percent for a 1 percent increase in the regulatory bias. Another interpretation could be that one standard deviation change of regulatory bias would result in an increase in house price growth by roughly 5.8 percent.[90]

In sum, these results suggest that regulatory bias positively impacts house prices. A natural interpretation is that regulatory bias affects the mortgage credit supply, stimulating housing demand and eventually driving house price growth. We demonstrate this channel in the next section.

4.5.2.2 Explaining the effect of regulatory bias on house prices through the credit supply channel

In our paper, we argue that the geographic heterogeneity in house prices may be linked to the growth of credit supply, which is induced by regulatory bias through CLL adjustments. To prove this channel, we adopt the Instrument Variable (IV) framework. The first-stage estimation regresses the credit supply on relative CLL changes, and the second-stage estimation regresses local house prices on predicted credit supply. This section presents the model identifications and empirical results for both stages.

In the first-stage regression, we aim to establish the effect of regulatory bias regarding CLL changes on credit supply growth. As CLL is designed to be the upper loan amount threshold, we argue that any adjustment in the CLL will directly impact credit supply. This argument is plausible and consistent with previous studies which also exploit CLL variations (Favara & Imbs, 2015; Grundl & Kim, 2021). The residual reflecting the level of regulatory bias in CLL

[90] This is calculated by multiplying the coefficient on regulatory bias with the standard deviation of regulatory bias and dividing it by the mean of the logarithmic return of Zillow home values.

adjustment supposedly influences the credit supply.

We include the same set of control variables and fixed effects as in Eq. (4.3). We obtain the predicted value of credit supply to use in the second-stage regression. We scrutinize the first-stage F-statistics to check how strong the instrument is. Stock et al. (2002) suggest that the F-statistics should be greater than 10 to ensure estimation reliability.

$$\mathrm{Credit\_supply}_{c,t} = \alpha_{IV1} + \beta_{IV1}\mathrm{Reg\_bias}_{c,t} + \delta_{IV1}L_{c,t} + \tau_{IV1,t} + \theta_{IV1,c} + \epsilon_{IV1,c,t} \quad (4.4)$$

Where $Credit\ supply_{c,t}$ is the total loan amount at the county level, $Reg\_bias_{c,t}$ is the estimated level of regulatory bias from Model (2) in Table 4.2, $L_{c,t}$ represents the aggregated county-level loan and borrower characteristics in the mortgage market, τ represents the year fixed effects to control country-wide time-varying factors such as the changes in the Federal funds rate, θ represents the county fixed effects to control unobserved county-level factors such as location-specific and regulatory factors. Subscript *IV1* refers to the first stage of the IV regression model. Subscript *c* is an index for the county, subscript *t* is an index for the year. To verify the result, we use three alternative proxies for credit supply including the total loan volumes, the number of originations and the number of approved loans. Both dependent variable and proxies for credit supply are in the log-return form.

Panel A of Table 4.4 presents the empirical results of the effect of regulatory bias on credit supply. The findings reveal that all variables indicating credit supply increase significantly with the regulatory bias level. The coefficient magnitudes are comparable across three proxies. The finding indicates that counties, on average, experience an increase of approximately 0.214 percent – 0.306 percent in the growth rate of credit supply when there is a 1 percent increase in regulatory bias. In addition, the F-stats of the first-stage estimations are all above 10, indicating that the instrument variable – regulatory bias – is strong and highly relevant to credit supply growth.

We posit that the regulators aim to resist a contraction in the credit supply. As FHFA has taken the "hold harmless" approach to preventing the CLL reduction (FHFA, 2022).[91] This implies a positive shock to the credit supply. The CLL is instantly adjusted when house prices appreciate but remains unchanged when house prices drop. These interventions assist more borrowers in obtaining conforming loans, which leads to an expansion in credit supply.

Table 4.4: Impact of regulatory bias on house prices through credit supply channel

Note: This table presents the estimations using IV regression. The regression unit is at the county level. The outcome variable is county-level house prices, the endogenous variable is credit supply, the IV is the regulatory bias. The proxy of house prices is the log return of Zillow home values. We use three proxies for credit supply: Total loan amount, number of originations, and number of approved applications. The regulatory bias is residual from Model (2) in Table 4.2. All variables are measured at log-return forms. Panel A presents first-stage regressions of credit supply on regulatory bias (i.e., first-stage estimation). The F-stat from the 1st stage is provided to verify the relevance condition. Panel B presents the results from the 2nd stage regressions of Zillow home values on instrumented credit supply. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

Panel A: First stage			
	Total loan amount	No of originations	No of approved apps
Regulatory bias	0.214** (0.085)	0.281*** (0.073)	0.306*** (0.078)
First-stage F-stats	91.41	73.84	76.50
County-level controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Adjusted R-squared (%)	51.81	52.88	49.27
No of obs.	28,623	28,623	28,623
Panel B: Second stage			
	Log return Zillow home values		
Total loan amount (Pred)	0.287** (0.143)		
No of originations (Pred)		0.219** (0.088)	
No of approved loans (Pred)			0.201** (0.08)

[91] Regulators may not be willing to decrease the CLL as they would like to maintain the eligibility of previously securitized loans for future securitization, prevent disruptions to credit availability, and support the recovery of the housing market. However, borrowers may be willing to bid a higher price against decreasing home value due to a larger CLL, which may potentially lead to an increase in house prices and worsen the housing affordability crisis.

County-level controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Adjusted R-squared (%)	18.91	26.28	26.81
No of obs.	28,623	28,623	28,623

In the second-stage regression, we regress house prices on the instrumented credit supply along with the above-mentioned control variables and fixed effects. This step is to investigate whether the credit expansion triggered by regulatory bias leads to a response in local house prices. We use Zillow home values to construct proxies for house prices.

$$\mathrm{House\_prices}_{c,t} = \alpha_{IV2} + \beta_{IV2}\widehat{\mathrm{Credit\_supply}}_{c,t} + \gamma_{IV2}L_{c,t} + \tau_{IV2,t} + \theta_{IV2,c} + \epsilon_{IV2,c,t} \quad (4.5)$$

where subscript *IV2* refers to the second stage of the IV regression model, subscript *c* is an index for the county, subscript *t* is an index for the year. The denotations are similar to the first-stage estimation specified in Eq. (4.4). The credit supply is proxied by the log returns of the total loan amount, the number of originations, and the number of approved applications at the county level, and the house prices are measured by the log return of Zillow home values.

Panel B of Table 4.4 presents the results from the second stage of the IV estimations. The instrumented estimates of credit supply are all positively and significantly associated with county-level house prices. We interpret that regulatory bias could create an exogenously positive shock to house prices channeled via the expansion of credit supply. Specifically, credit supply growth could be induced by a higher loan amount, more originated loans or more approved applications. The changes in house prices are 0.201 percent to 0.287 percent for a 1 percent change in the estimated credit supply. A higher loan amount allows borrowers to bid higher on houses, leading to greater competition and consequently driving house prices upwards.

Comparing the coefficients of the first- and second-stage estimations, we notice that the transmission effect is weakened regarding the number of originations and the number of approved applications. We observe smaller magnitudes on the coefficients of instrumented credit supply as the exogenous shocks from regulatory bias on these features are stronger. This may suggest that the expansion of credit supply, through allowing more people to have credit access compared to offering a higher loan amount, helps maintain better sustainability in the housing market.

4.5.3 Heterogenous effects of regulatory bias on house prices

4.5.3.1 Divergence and convergence between CLL and house price growths

As we observe the cumulative CLL and HPI growth in Panel B of Figure 4.1 and data descriptions in Section 4.4, we find that there are misalignments during the pre-2017 period but tighter alignments since 2017.[92] These patterns portray the difference in CLL adjustments under different housing conditions, implying different levels of regulatory bias. We split our sample into two sub-samples with 2017 as a division and run the panel regressions for each period. The results are reported in Table 4.5.

Table 4.5: Impact of regulatory bias on house prices, period subsamples

Note: This table presents the estimations of house prices on regulatory bias for two sub-samples: pre-2017 and since-2017. The regression unit is at the county level. The dependent variable is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Pre-2017 (2010 – 2016)		**Since-2017 (2017 – 2021)**	
	Log return Zillow home values			
Regulatory bias	0.203*** (0.022)	0.201*** (0.022)	0.029 (0.055)	0.015 (0.054)
County-level controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared (%)	49.49	50.18	45.98	46.51
No of obs.	13,916	13,916	14,707	14,707

[92] The HMDA data does not provide information on FICO score or house value at the loan level; hence we did not examine the subsets based on the securitization standards. However, conforming loans are homogeneous and are exposed to the same level of credit availability regardless of the borrower-specific characteristics, splitting the sample by these pre-determined features may not help to investigate the dynamics of CLL effects on housing values.

The impacts of regulatory bias on local house prices are only significant for the pre-2017 period. We find no evidence of rising house prices due to CLL-related regulatory bias for the since-2017 period. In specific, one standard deviation change in the regulatory bias is associated with an 11 percent increase in the house price growth. Note that the corresponding result from the full sample is only 5.8 percent. This finding implies that the positive effect of regulatory bias on house prices may be muted if CLL adjustments align well with the historical trend of the housing market. In other words, a careful alignment between CLL growth and previous HPI growth is critical to mitigating the opportunity to form a housing bubble and ensure sustainability.

While the CLL's initial purpose is to attempt to lay boundaries around 'typical' loan purchase characteristics, concerns about inflating house prices have been raised since 2007 when the law around its calculation changed significantly.[93] This paper finds that no such bias exists if policymakers align CLL changes with changes in the housing markets.

4.5.3.2 Lender constraints: Access to funding

Lender constraints could influence the impact of regulatory bias on house prices. We approach the examination of lender constraints from the perspective of access to funding sources. This constraint results in a classification of mortgage lenders into two main types: banks and non-banks. Banks have access to both deposits and securitization through GSEs, while non-banks largely rely on securitization. Banks are considered to be unconstrained and non-bank lenders are constrained. We calculate the percentage of bank lending (i.e., in terms of total lending volumes) for each county-year. Counties that have a percentage of bank lending higher than the 75^{th} percentile (i.e., 68.8 percent) are considered to be bank-dominated, while the

[93] Chapter 6 of the Final report of the National Commission on the causes of the financial and economic crisis in the United States, retrieved from https://www.govinfo.gov/content/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf

remaining consists of the nonbank-dominated group.[94] We examine how different lenders play their role in driving house prices as a response to regulatory bias and report the estimates in Table 4.6.

The effect of regulatory bias on house prices is considerably larger in bank-dominated counties than in nonbank-dominated ones. There are two reasons to explain this finding. The funding sources available to banks and non-banks are perhaps the most important reason explaining these differential effects. Banks can tap into multiple funding sources, including both deposits and securitization. When there is an enhanced funding capacity, banks can handle larger loans more effectively with their in-depth expertise. From a nonbank perspective, they are vulnerable to liquidity pressure (Kim et al., 2018) as they solely rely on short-term warehouse credit for funding the new loans and quickly securitize them to roll over their lines of credit. In despite of the benefit of increasing the loan limit, nonbank lenders with constrained access to funding may limit them from further expanding their credit supply. As a result, nonbanks' credit supply may not strongly react to CLL-related regulatory bias, hence limiting the transmission effect to the housing market.

Table 4.6: Impact of regulatory bias on house prices, lender constraints: access to funding

Note: This table presents the estimations of house prices on regulatory bias for two sub-samples: bank-dominated counties and nonbank-dominated counties. The former includes counties where the percentage of bank lending (i.e., loan volume) is greater than the 75th percentile. The remaining consists of the latter. The regression unit is at the county level. The dependent variable is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

[94] Nonbank lenders are dominating the mortgage market. Since 2017, nonbank mortgage share has surpassed 50% (Sinnock, 2022). This share was 68.1% in 2020 (McCaffrey, 2021). Hence, we use the 75th percentile, which is equal to 68.8 percent to determine if the corresponding county is bank-dominated. As there are more non-bank lenders than banks in the market, counties that have a percentage of bank lending higher than the 75th percentile are bank-dominated. Since the presence of nonbank lenders is significantly higher than that of banks, choosing this threshold will clearly distinguish lender constraints between the two players in the market. The results using the thresholds of 25th and 50th percentiles are not statistically significant.

	Bank-dominated counties (Unconstrained)		**Non-bank-dominated counties (Constrained)**	
	Log return Zillow home values			
Regulatory bias	0.168*** (0.052)	0.177*** (0.052)	0.077*** (0.026)	0.073*** (0.026)
County-level controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared (%)	74.08	74.41	45.96	46.79
No of obs.	2,806	2,806	25,817	25,817

In addition, the origination cost for banks is typically higher than nonbank lenders as they face more regulations (D'Acunto & Rossi, 2021; Haughwout et al., 2022)[95], so they are more hesitant to originate smaller loans and often aim for larger loans. However, with an increase in the loan limit, banks could be more inclined to expand their credit supply to offer more super-conforming loans and occupy a more extensive customer base. This suggests that banks could be more responsive to the relative CLL changes, hence intensifying the impact on house prices.

These findings indicate that banks are more likely to absorb regulatory shocks than nonbank lenders and play a more crucial role in driving house prices. Our results also reinforce the role of securitization in expanding credit supply, as argued by Calem et al. (2013), Fuster & Vickery (2015), and Loutskina & Strahan (2009).

4.5.3.3 Moderating effect of recourse law

For borrowers, the state-level law of deficiency judgments (recourse lending) could have a similar impact on their behaviors. We examine borrower constraint through the state-level recourse law. Those who live in non-recourse states have lower personal liabilities in the default event, as the lenders can only seize the underlying properties to recover the loss. Meanwhile,

[95] Examples are Dodd-Frank Act or Comprehensive Capital Analysis and Review stress tests.

lenders can take legal action against recourse borrowers to collect the remaining debt if the outstanding balance from the property is deficient to cover the loss. We contend that recourse borrowers are more constrained in obtaining more credit because of the fear of increasing default risk. The extra credit availability would lead to an increase in default risk as the exposure at default becomes more prominent, and the repayment burden is also enlarged. Therefore, we expect that the role of non-recourse borrowers in moderating the effect of relative CLL change on house prices may be more pronounced.

We run the regression of house prices on the regulatory bias for recourse and nonrecourse states[96] and report the results in Table 4.7.

While a 1 percent increase in regulatory bias leads to a 0.152 percent increase in house prices in non-recourse states, the corresponding increase in recourse states is only 0.088 percent. A possible explanation for this is that non-recourse borrowers are more eager to obtain higher credit as they have lower personal liabilities in the default event. Borrowers are more willing to up their bids on properties, increasing competition and inflating house prices. Our findings verify the role of demand constraint caused by recourse regulation in influencing the relationship between regulatory bias and house prices and certify that non-recourse borrowers drive our results.

Table 4.7: Impact of regulatory bias on house prices, borrower constraints: recourse

Note: This table presents the estimations of house prices on regulatory bias for two sub-samples: recourse and non-recourse. The former includes counties belonging to recourse states, while the latter includes those belonging to non-recourse states. The regression unit is at the county level. The dependent variable is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Non-recourse (Unconstrained)		Recourse (Constrained)	
	Log return Zillow home values			
Regulatory bias	0.134***	0.152***	0.088***	0.072**

[96] There are 12 non-recourse states in the US including AK, AZ, CA, CT, ID, MN, NC, ND, OR, TX, UT, and WA.

	(0.031)	(0.031)	(0.029)	(0.029)
County-level controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared (%)	54.68	56.18	46.80	47.53
No of obs.	6,656	6,656	21,967	21,967

4.5.3.4 Borrower financial constraints

We finally implement the analysis regarding borrowers' financial circumstances. We measure the borrower constraints according to a popular theory of mortgage default – Double-Trigger theory – with equity and liquidity restraints. The leverage constraint is measured by the loan-amount-to-value (LTV) ratio, and the illiquidity constraint is measured by the loan-amount-to-income (LTI) ratio instead of the debt-to-income ratio (DTI) as HMDA does not provide the lending rate prior to 2017 that is required for the debt payments. We use the county-level Zillow home values to calculate the LTV ratio since HMDA does not provide property values for data prior to 2017. LTV and LTI ratios are calculated using county-level average values. We specify counties with average LTV and LTI higher than the 75th percentile as constrained and those below as unconstrained. We then run the estimations for unconstrained and constrained sub-samples to explore the moderating effect of borrower financial constraints on the relationship between regulatory bias and house prices.

Table 4.8: Impact of regulatory bias on house prices, borrower constraints: LTV and LTI

Note: This table presents the estimations of house prices on regulatory bias for two sub-samples: unconstrained and constrained counties. We calculate loan-to-value and loan-to-income ratios using averages of county-level data. Constrained counties are those with LTV and LTI higher than the corresponding 75th percentile values. The regression unit is at the county level. The dependent variable is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request.

	Low LTV and Low LTI (Financially unconstrained)		**High LTV and High LTI (Financially constrained)**	
	Log return Zillow home values			
Regulatory bias	0.08** (0.038)	0.077** (0.037)	-0.06 (0.369)	-0.072 (0.356)
County-level controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes

County fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared (%)	58.33	58.90	78.31	80.70
No of obs.	13,833	13,833	628	628

The results are insignificant for constrained borrowers. This means that these borrowers could not absorb the additional expansion of credit supply induced by the regulatory bias; therefore, the impact on the housing market is also muted. In contrast, unconstrained borrowers are more likely to take advantage of the new credit available to buy more expensive homes. The fewer financial constraints portray them as less risky borrowers and pave the way for them to access more credit, perhaps with a lower interest rate. Furthermore, unconstrained borrowers have better liquidity (i.e., income) and equity (i.e., deposit) to match the higher requirements of a larger loan. Even with stable credit conditions, a larger loan size typically requires more equity and income to satisfy the LTV and LTI requirements. As a result, unconstrained borrowers tend to take advantage of the increased CLL or expansion of credit supply and be the main driver of the growth of house prices in the market.

Our results suggest that regulatory bias can have significant effects on credit availability for borrowers with different levels of constraints. Those with high constraints will find it harder to afford to buy a home as house prices keep increasing due to regulatory bias. Borrowers find it challenging to obtain homeownership with the CLL changes (Grundl & Kim, 2021). Those with low constraints may be more likely to take on excessive debt and significantly contribute to the house price appreciation or even a potential housing bubble. Policymakers should be aware of the potential limitations of such interventions and consider other measures to address housing affordability and access to credit for a broader range of borrowers.

4.6 Robustness tests

We conduct two additional robustness checks. We employ the data on FHFA HPI to construct the proxies for house prices. The replication is done for the investigation of the differential effect between regulatory bias and house prices with different regimes and moderating effects of lender and borrower constraints. We report the results in Table 4.9. The time-series analyses for pre-2017 and since-2017 subsamples reveal that the effect is only significant for the former period. These findings reinforce the significance of aligning CLL growth with the historical house price growth. We also confirm that the effect of regulatory bias on house prices is stronger for bank-dominated counties, non-recourse counties and groups of unconstrained borrowers.

Although we argue that the incorporation of county-level macroeconomic variables is not needed in the model as their effects are captured in the proxy of regulatory bias, other may raise a concern about the correlation of these factors with the county-level house prices. Therefore, we include the macroeconomic factors into the model as a robustness test. We replicate the tests for time series, bank-, recourse- and constraint-related subsamples. The results presented in Table 4.10 are highly consistent with the main analysis. After fully controlling for all possible effects at county levels on house prices, we can still verify the positive effect of regulatory bias on the local house prices for the full sample and sub-samples.

We obtain a high consistency in the results compared to the main analysis. If there is a difference, the coefficient magnitudes are slightly smaller than those in the main analysis but very marginal. This robustness test confirms the impact of regulatory bias on house prices as well as highlights the roles of borrowers' and lenders' constraints in shaping the relationship between CLL and house prices.

Table 4.9: Robustness test: Alternative house price proxy using FHFA HPI

Note: This table presents the results from the regression of house prices on regulatory bias using the full sample but using different proxy for house prices. The regression unit is at the county level. The proxy of house prices is the log return of FHFA HPI. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Full sample	**Pre-2017 sample**	**Since-2017 sample**	**Bank-dominated counties**	**Nonbank-dominated counties**	**Non-recourse counties**	**Recourse counties**	**Financial unconstrained**	**Financial constrained**
	Log return FHFA HPI								
Regulatory bias	0.123*** (0.017)	0.223*** (0.022)	0.029 (0.035)	0.176*** (0.046)	0.096*** (0.021)	0.185*** (0.029)	0.073*** (0.022)	0.103*** (0.034)	0.068 (0.258)
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared (%)	44.40	35.07	50.55	59.75	43.55	51.35	41.96	42.09	74.42
No of obs.	29,711	16,190	13,521	3,572	26,139	6,765	22,946	15,597	523

Table 4.10: Robustness test: Incorporating county-level macroeconomic variables

Note: This table presents the results from the regression of house prices on regulatory bias using the full sample but incorporates various county-level macroeconomic variables. The regression unit is at the county level. The proxy of house prices is the log return of Zillow home values. The regulatory bias is residual from Model (2) in Table 4.2. County-level control variables are county-aggregated loan and borrower characteristics including percentages of bank lenders, securitization, joint applications, residential properties, refinancing loans, conventional loans, female applicants, Latino applicants, and Black applicants. County-level macroeconomic variables include log returns of real GDP, housing stock, median household income and lagged population. Intercept and the coefficients on county-level controls and year dummies are not shown for simplicity but are available on request. Standard errors are in parentheses. ***, **, and * indicate 1%, 5% and 10% significance level respectively.

	Full sample	**Pre-2017 sample**	**Since-2017 sample**	**Bank-dominated counties**	**Nonbank-dominated counties**	**Non-recourse counties**	**Recourse counties**	**Financial unconstrained**	**Financial constrained**
	Log return Zillow home values								
	0.117***	0.189***	0.062	0.152***	0.089***	0.151***	0.091***	0.089**	0.030
Regulatory bias	(0.022)	(0.022)	(0.056)	(0.053)	(0.026)	(0.031)	(0.03)	(0.038)	(0.365)
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level macros	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared (%)	48.90	50.65	46.66	74.81	46.96	56.80	47.70	59,14	81,50
No of obs.	26,623	13,916	14,707	2,806	25,817	6,656	21,967	13,833	628

4.7 Conclusion

Regulatory bias in the economy frequently generates debate. Unintentional effects should be minimized whilst achieving the desired outcomes. We investigate the effect of regulatory bias reflected through the CLL adjustment on house prices. After careful control for endogeneity, we find a sizably positive effect of regulatory bias on house prices which could be explained through the credit supply channel. This effect is strong and positive during the pre-2017 period when CLL growth diverges from national HPI growth but vanishes during the since-2017 period when CLL growth directly coordinates with national HPI growth. We additionally investigate the effect of heterogeneity across different lenders and borrowers. Our results indicate that bank lenders are the main driver of house price appreciation with respect to regulatory bias. Regarding the borrower perspective, unconstrained borrowers (i.e., located in non-recourse states or are less financially constrained) take greater advantage of the increased credit availability induced by regulatory bias and drive up house prices in the market.

Our study recommends that policymakers should tightly align CLL growth with national HPI growth even when house prices fall so that any distortion to housing prices can be prevented. Specifically, policymakers may need to consider allowing CLL levels to decrease when the housing market declines, unlike the standard process taken in the past. This may better reflect the housing market's current state and promote greater financial inclusion for all borrowers.

There are significant differences in the transmission effects between nonrecourse and recourse borrowers, signifying a need for taking the state-level regulatory environment into account when implementing these interventions. In addition, the heterogeneity effect exists regarding borrowers' financial situations in which borrowers are not able to take advantage of increasing annual CLL variations to get a bigger loan amount due to being constrained. This may lead to an increasing gap in housing affordability between constrained and unconstrained borrowers, where the CLL continually increases as unconstrained borrowers continue the cycle of increasing house prices. It may be worth considering alternative policies that can promote sustainable housing affordability and access to credit, such as targeted subsidies for low-income borrowers, policies that promote the construction of affordable housing, or variations in pathways to owning a house.

Further research may look at the unconventional loans securitized by Federal Housing Administration and investigate the impact of CLL changes on financial system fragility. We can also investigate the effect of CLL-related intervention on consumer protections or the distribution of mortgage lending markets.

Chapter 5 : Conclusions

The theme of this thesis is about the financial barriers faced by multiple participants in mortgages markets. We place the context of our studies in the US as their mortgage market structure is highly developed and sophisticated. Apart from two main participants—lenders and borrowers, GSEs such as Fannie Mae and Freddie Mac also play a crucial role as they provide sufficient liquidity for lenders through securitization. Each study in this thesis tackles different issues with the aim of diminishing the financial constraints embedded in the mortgage market. These issues are (i) the current capital framework for GSEs does not reflect the risk variations and requires high capital charges; (ii) the most popular mortgage type (i.e., FRM) does not incorporate personalized characteristics of borrowers into the design and provide lenders no hedging tool against default risk; and (iii) government interventions in the mortgage market can distort housing prices and hinder the development of an inclusive financial system. This chapter outlines these issues and summarizes the solutions that this thesis offers to address them, reinforces the impacts on regulations and industry practices, and suggests avenues for future research.

5.1 Summary of key findings

In Chapter 2, we respond to the urge to establish risk-based capital models for GSEs as a mandate by 2025. Many experts in the industry state that the current capital rule for GSEs with the prescribed risk weights leads to considerably high capital requirements. This is partly because the GSE capital rule is designed to be the same as the Basel-rule for banks. With the same mortgage, however, the GSE risk is much lower than a bank's as GSEs can minimize risk through issuing of an MBS. The concerns around procyclicality is a significant issue within the current framework, as it appears to be ineffective in addressing this problem. Under the current framework, the high capital requirements could potentially hinder mortgage lending as there could be a reduction in securitization from GSEs. This could lead to higher financial burdens for the public through a flow-on increase in the mortgage rate.

To address this problem comprehensively, we propose a unified model incorporating both observed and unobserved systematic risk factors. The more we control macroeconomic conditions, the higher the level of the observed factor. As we measure the observed factor by mean PD, which is also the most important component in calculating the capital charges, the incorporation of macroeconomic conditions will lead to a wider variation in mean PD over time that implies a higher degree of procyclicality in capital requirements. Under the two-factor risk model, we demonstrate that the asset correlation decreases with increasing control of the observed factor, leading to a lower economic capital compared to regulatory capital. This serves to offset the increased cyclicality of capital requirements resulting from the amplified variations in PDs. The capital ratios calculated based on the unified framework is significantly lower than that estimated under the Basel framework, with the figures of 2 percent and 6.7 percent respectively. The unified framework proves to align closer with industry risk management practices as it captures more sensitivity of mortgage rate to systematic risk. We also discover that mortgages differ in terms of exposure to systematic risk factors, in which mortgages originated by nonbank lenders, located in states with nonrecourse laws and/or California carry a higher systematic risk.

In Chapter 3, we propose two novel ex-ante mortgage contracts that take the borrowers' liquidity characteristics into consideration. Most mortgage contracts are currently designed with borrower financial features at origination. Alternatively, if borrowers encounter financial difficulties due to unexpected circumstances such as job loss during the COVID-19 pandemic, they could receive forbearance for a certain amount of time. However, this ex-post intervention creates a burden on the government budget and taxpayers. While recent literature has started to address the issue of procyclicality, it is worth noting that many studies have been theoretical in nature. Empirical evidence on this topic remains limited.

Two ex-ante contracts are designed based on income growth at the state level and the age-related hump-shape mortgage risk respectively. The IFRM aligns the repayment schedule with the state's income growth, while the AFRM designs the repayments to offset the age-related risk. These designs are supposed to relieve liquidity constraints for borrowers. We find that both contracts could lower PD, systematic risk, and regulatory capital for lenders. The effect of AFRM is stronger than that of IFRM. If AFRM is adopted in practice, lenders could potentially enjoy an increase of 10 percent in the ROC ratio. Otherwise, they could transfer this saving to borrowers by lowering the credit spread by 17 bps.

In Chapter 4, we examine the effect of CLL-related interventions on house prices. According to the current framework, CLL increases when HPI increases, but remain unchanged when HPI drops. This practice exhibits a regulatory bias which potentially distorts housing prices. The effect could then be influenced by different market participants. After addressing the endogeneity problem, the empirical results of Chapter 4 indicate a positive relationship between CLL and house price growth. However, this relationship is only significant when CLL adjustment diverges from house price growth (i.e., before 2017). We also reveal that market participants who face fewer constraints, including banks, borrowers in nonrecourse states and those having lower financial constraints, induce stronger effects.

5.2 Thesis implications for industry practices and regulations

The findings from this thesis carry several implications for industry practices and regulations. First, our analysis from Chapter 2 provides different variations of risk-based capital frameworks that the FHFA could choose to regulate GSEs. The main implication is that utilizing a comprehensive framework enables the capture of systematic risk more efficiently, leading to more reasonable capital charges and greatly apprehending variations in mortgage rates. This allows GSEs to enhance their risk management abilities and better price GSE-eligible loans. The flow-on effects could benefit mortgage lenders in terms of motivating them to enhance their risk models to maintain access to securitization from GSEs.

Second, the introduction of personalized mortgage contracts in Chapter 3 could lower the financial constraints for borrowers, especially for the underserved population; hence promoting inclusive finance and increase access to affordable housing. With the help of advanced modelling and techniques, the realization of these contracts is within reach. The benefits are not just limited to borrowers as if these contracts are adopted, they could allow lenders to increase their competitiveness and drive further mortgage innovations. With the risk reduction benefit, these contracts have the potential to improve the resilience of the financial system. Therefore, we recommend conducting pilot programs to review the contracts' effectiveness as well as implement a thorough assessment of the regulatory impacts before broader adoption.

Third, the findings from Chapter 4 suggest policymakers remain cognizant of the unanticipated impact of their CLL-related interventions on increasing housing prices. By firmly following the historical trend, distortions to house prices could be avoided. This supports sustainable growths of both mortgage and housing markets.

Last, the findings from this thesis highlight the market dynamics through revealing the heterogeneity across market participants. We highly suggest regulators account for this diversity and their financial constraints when formulating policies. This approach leads to more balanced and effective regulatory frameworks that better serve the needs of distinguished market participants. In this way, we could further promote financial inclusivity, competition, and financial stability.

Overall, all three studies in this thesis provide a comprehensive understanding about financial constraints and suggests several innovations to motivate the development of mortgage markets. These findings enrich the literature of mortgage finance research, benefits practitioners working in the credit sector, as well as contribute to the establishment of a more efficient and stable banking system.

5.3 Future research

The two-factor risk model proposed in Chapter 2 could be utilized to determine more granular systematic risk levels for other types of debt securities such as mortgages held in bank portfolios or corporate bonds. This comprehensive framework could allow a better incorporation of macroeconomic conditions and alignment with industry practices, enhancing a more sufficient capital allocation and promoting smoother compliance.

From Chapter 3, we developed two ex-ante mortgage contracts to tackle the liquidity constraint of borrowers. Future contracts could be further personalized by incorporating features to lower equity constraints into the design. In this way, we could increase access to credit for many households and promote sustainability of homeownership growth.

As Fintech lenders rapidly develop and disrupt the mortgage market, more lenders have started adopting technology to streamline the mortgage process. The utilization of advanced predictive modelling such as machine learning has also changed the shape of the mortgage market. Understanding the benefits and risks from these technological adoptions will be crucial. Hence, future research could further scrutinize the impact of technological adoption on industry competition, consumer protection, and the macroeconomy.

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