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**IMPACT OF COVID-19 PANDEMIC ON MORTGAGE
MODIFICATION AND THE PROBABILITY OF
REDEFAULT**

Ricardo Macias Marques Sequeira

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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by
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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics.

Supervised by
Professor Doutor Jorge Miguel Ventura Bravo

November, 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, July 2024]

ABSTRACT

This study investigates the impact of the COVID-19 pandemic on mortgage modifications and the probability of redefault. Research aims to understand how pandemic-induced economic disruptions influenced mortgage holders' ability to maintain modified loan terms. Using logistic regression models, we analyzed data from a sample of Fannie Mae mortgage loans, comparing pre-pandemic and pandemic modifications. The results indicated a significant decrease of 27% in the probability of redefault when the loan is modified after the onset of the pandemic, highlighting the crucial role the government played in this crisis. The key variables included original loan terms, credit scores, and debt-to-income ratios. Furthermore, COVID-19 was found to have a significant effect on variables such as debt-to-income ratio and the modification of the loan term, when comparing pre and post covid modifications. This study contributes to the field by providing information on the financial strengths exposed by the pandemic and offers policy implications for the management of future economic crises. The findings underscore the robust financial support systems created to mitigate the adverse effects of such unprecedented events on mortgage stability and the direction that governments should take to expand such measures.

KEYWORDS

COVID-19; mortgage modification; redefault probability; logistic regression; economic impact

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LIST OF ABBREVIATIONS AND ACRONYMS

CARES Act Coronavirus Aid, Relief, and Economic Security Act

US United States

HAF COVID-19 Homeowner Assistance Fund

1. INTRODUCTION

The COVID-19 pandemic has profoundly disrupted global economies, affecting various sectors and financial systems. Among the numerous areas impacted, the housing market and, more specifically, mortgage financing have experienced significant turbulence. According to the Urban Institute, mortgage delinquency rates soared to levels not seen since the Great Recession, highlighting the urgency for effective loan modifications and support measures. A study by the Federal Reserve Bank of Philadelphia noted a sharp increase in forbearance requests, with over 8% of mortgages entering forbearance at the peak of the crisis. This unprecedented situation underscores the importance of understanding the dynamics of mortgage default and modification, as these factors play a crucial role in maintaining financial stability and preventing a housing market collapse. By examining the interplay between borrower characteristics, loan modifications, and economic conditions, this research aims to provide critical insights into mitigating mortgage default risks during times of economic upheaval.

Recent research has highlighted various important triggers and contributing factors to the key financial indicator of mortgage defaults. Campbell and Cocco (2015) emphasise the "dual triggers" of negative home equity and constrained borrower resources, while Chu and Park (2008) identify declining home prices and high Mortgage (Debt)-to-Income ratios as primary drivers. On the other hand, Foote et al. (2009) argue that debt-to-income ratios at origination are not strong predictors of default, emphasising instead house prices and household income variations. O'Malley (2021) discusses the motivational effect of repossession risk, while Haughwout, Peach, and Tracy (2008) underscore the influence of bad credit and adverse economic conditions on early defaults. Despite recognised benefits, lenders have been reluctant to offer loan modifications due to potential costs and risk (Adelino et al. 2013), and the complexity of securitisation further complicates these efforts (Levitin, 2009). However, Foote et al. (2009) and Kim (2017) suggest that modifications can be economically beneficial, though the financial gains for investors are debated. Haughwout et al. (2009) find that significant payment reductions, especially through principal forgiveness, lower redefault rates, highlighting the importance of borrower equity in successful modifications.

A thorough analysis of the body of research shows that shock events are regularly identified as critical variables driving mortgage defaults. Due to this general agreement and the absence of previous research on the most recent shock event, I am driven to investigate the impact of COVID-19 as a shock event on the mortgage market. In particular, our objective is to investigate how COVID-19 affects the likelihood of defaulting after loan modifications, by testing whether or not this likelihood is statistically lower for loans modified after the onset of the pandemic. Also, our objective is to examine the effect of COVID-19 on the main triggers to default. Understanding the impact of the pandemic on mortgage modifications and probability is essential to develop strategies to enhance financial stability and support

homeowners in future crises. This thesis will contribute to the broader discourse on financial resilience and provide recommendations for policymakers, lenders, and other stakeholders involved in the housing market.

It is presented in the first chapter a compilation of literature addressing mortgage modification, with a focus on the main triggers to default, which is a critical indicator of financial distress and has been extensively studied to understand its multifaceted causes and implications. In the following chapter, descriptive statistics on the characteristics of the loan and the borrower are presented. The research then delves into the effectiveness of mortgage modifications and how the COVID-19 pandemic impacted the subsequent probability of redefault. By analysing Fannie Mae and using logistic regression models, this study aims to identify patterns and outcomes associated with these modifications. In the following pages, we will analyze our findings to draw conclusions and offer recommendations.

2. LITERATURE REVIEW

2.1. MORTGAGE DEFAULT

Mortgage default is a key indicator of financial distress and is closely monitored by the housing and financial markets as it can have far-reaching implications for individuals, communities, and the broader economy (Low, 2022). It can occur for various reasons, and understanding these factors is crucial to develop the most fitting strategies to tackle this complex problem.

The intricacy of this issue is such that its conception still brings out new ramifications. Campbell and Cocco (2015) introduce the concept of "dual triggers" of default, emphasising that the default decision depends not only on negative home equity, but also on the borrower's constraints imposed by low current resources. This is also supported by the research of Herkenhoff (2012), who found that negative equity alone increases the likelihood of default by 1.45%, while the interaction between unemployment and negative equity makes a person 10% more likely to default, highlighting the importance of these double trigger events in persistent defaults.

Chu and Park (2008) highlight the nationwide decrease in home prices as a primary driver of mortgage defaults. Additionally, they note that the rise in borrowers with high mortgage-to-income (MTI) ratios has contributed to increased default rates in the subprime market. On the other hand, Foote et al. (2009) challenge the notion that debt-to-income (DTI) ratios at origination are strong predictors of future mortgage default. Their findings suggest that, while a higher monthly payment increases the likelihood of default, other factors such as house prices, expectations of future price growth, and variations in household income also play a significant roles in default outcomes.

Auh and Park. (2023) investigate how interest rates impact the likelihood of mortgage delinquency in the United States by disentangling the causal effect of interest rates from the "price of risk" effect. Their results indicate that a 1% increase in the original interest rate leads to a 2.66% increase in the probability of a borrower defaulting, keeping other factors constant.

Otero et al. (2016) analysed the relationship between loan-to-value (LTV) ratios and default risk in residential mortgage-backed securities in Spain from 2005-2008. They found that higher initial LTV ratios are associated with increased default risk, indicating that borrowers with higher LTV ratios are more likely to default on their mortgages. Additionally, the research highlighted a non-linear relationship between the probability of default and the LTV ratios, with a significant increase in default risk observed for LTV values exceeding 80%.

Guler (2015) examines the impact of information technology on the mortgage market. The study suggests that as lenders gain better information about households, various mortgage parameters, including premiums, foreclosure rates,, and homeownership rates are influenced.

Foote et al. (2008) provide a nuanced perspective on the relationship between negative home equity and foreclosure. Contrary to the assumption that all households with negative home equity default, their research reveals that fewer than 10% of homeowners in this situation lose their homes to foreclosure. This finding underscores the importance of considering additional factors beyond home equity when assessing the risk of mortgage default. Also, a study conducted by O'Malley in 2021 proposes that the risk of repossession acts as a motivating factor for households to continue making their mortgage payments. This hypothesis is based on an analysis of data from Ireland, which centres around an unforeseen legal decision that restricted the enforcement of collateral on delinquent residential mortgages that originated before a specific date. O'Malley's research findings indicate that, following the implementation of this legal ruling, borrowers exhibited a quarterly increase in default rates of approximately 0.3 percentage points, representing a relative increase of roughly one-half.

Ganong and Noel (2020) present a novel method for causal attribution of mortgage defaults. Their central finding challenges conventional wisdom, revealing that only 3 percent of defaults are caused exclusively by negative equity. This finding suggests that adverse events are a necessary condition for the vast majority of mortgage defaults. Furthermore, research by Haughwout, Peach, and Tracy (2008) sheds light on the factors that influence early mortgage defaults, specifically in the context of the 2005 timeframe. Their findings indicate that bad credit and adverse economic conditions were contributing factors. However, research suggests that the changes in the broader economic landscape influenced the increase in increasing early mortgage defaults during this period. In other words, while borrowers' credit histories did play a role, the economic environment appeared to exert a more substantial influence on the rising default rates.

Chamboko and Bravo (2016, 2019a,b, 2020) developed a novel multi-state framework to model state occupations and the transitions among current, delinquency, default, prepayment, repurchase, short sale, and foreclosure on mortgage loans. Using a multistate Markov model to model the transitions to and from various states, the authors conclude that the key factors affecting the transition into various loan outcomes are the ability to pay as measured by debt-to-income ratio, equity as marked by loan-to-value ratio, interest rates, and the property type.

Ashofteh and Bravo (2019, 2021) introduce a novel time-dependent credit scoring method to identify good loans with a low false negative rate. The method uses a two-step approach based on an initial Kruskal-Wallis nonparametric statistic analysis to form a computationally efficient credit scoring model based on an artificial neural network, Logistic regression with Ridge penalty, Random Forests (RF), and Support Vector Machine (SVM) to learn the model and to assess model performance.

Raimundo and Bravo (2024) investigate the predictive accuracy of single-based classifiers against the stacking generalisation approach in credit risk modelling using real-world peer-to-peer lending data. The authors find that stacking ensembles consistently outperform traditional individual credit scoring models in predicting the default probability and that adopting a feature selection process and hyperparameter tuning contributes to improving the performance of individual credit risk models and the superlearner scoring algorithm.¹

The abundance of literature surrounding mortgage default underscores its significance as a critical aspect of housing and financial markets, offering valuable knowledge and guidance to navigate this complex terrain. However, despite this abundance, one perplexing question arises: why weren't lenders making more modifications? The reluctance of lenders to make more modifications to mortgage loans is a topic of considerable interest and concern. Numerous hypotheses have been extensively studied and scrutinised within the context of this issue.

It is important to first say that in the annals of mortgage history, one prevailing fact stands out: mortgage modifications were a rare phenomenon. Unlike the more prevalent practices and options available today, such as loan refinancing or loan forbearance, mortgage modifications were infrequently utilised as a tool to address borrowers' financial difficulties. In a data set containing mortgage loans from 2006-2011 and covering approximately 60% of the US mortgage market, Adelino et al. (2013) note that less than 2% of seriously delinquent borrowers received concessionary modifications, while approximately 8% received some form of modification. In their study, they also discuss the "institutional theory," which contends that market frictions prevent lenders from renegotiating loans even when doing so is in their best interest, which is one of the most widely accepted hypotheses in the literature and in decision-making circles to explain why lenders don't renegotiate mortgages. The idea states that lenders compare the costs of making the same concession to all observationally comparable borrowers with the advantages of preventing a specific foreclosure. These expenses include the potential for borrowers to "self-cure" (i.e. leave the delinquent status without assistance) or for borrowers to redefault following a modification (Adelino et al. 2013).

This presents significant financial concerns for lenders. All these important considerations are not taken into account by the typical formula, which argues that investors only suffer losses when a foreclosure occurs. When investors choose to modify mortgages for borrowers who self-cure, they lose money. This formula also fails to account for the very real chance that borrowers with modified loans could go into default again in the future, usually for the identical reasons that led to their initial default (Foote et al., 2009). Additionally, in a comparative analysis of two economies, Kim (2017) observed a noteworthy variation in the

¹ The adoption of model combination and meta learning approaches is expanding in multiple areas including credit risk management (see, e.g., Ayuso et al. 2021; Bravo et al. 2018, 2020, 2021, 2022, 2023).

steady-state default rate. This variation is contingent upon the level of modification costs within each economy. Specifically, the default rate ranges from nearly negligible when modifications are costless to approximately 1.5% when the process of modification becomes exceedingly expensive, which most likely means that costs are an obstacle to modify.

Securization is also a controversial term in relation to this matter. Although Adelino et al. (2013) found that a comparison of renegotiation rates for PLS (Private Label Securities) and portfolio loans did not yield economically significant differences, suggesting that securitisation may not be a significant obstacle, other studies have suggested the contrary. As highlighted by Adam J. Levitin (2009), a major factor behind the failure of the private market to address the foreclosure crisis is that for most mortgages there are no longer “lenders” of which to speak. Most mortgage loans are no longer exclusively owned by a single entity; instead, they are securitised, so that thousands of investors have a fractional interest in a pool of loans. In his opinion, this fragmentation of ownership adds layers of complexity to the mortgage industry and can present significant challenges in addressing the foreclosure crisis effectively.

Addressing the challenges associated with loan modifications and making them more accessible can indeed yield significant positive outcomes for both borrowers and the broader financial system (Foote et al., 2009). The decision between offering loan modifications to struggling borrowers or pursuing foreclosure is complex, fraught with economic and social implications. Central to this debate are the varying perspectives on the gains or losses investors may incur and how these actions ripple through the broader financial landscape.

In the realm of economic analysis, Kim’s research (2017) sheds light on the relationship between housing price fluctuations and default rates. In an experimental study, Kim examined how the default rate responds to an unexpected 30% drop in house prices, simulating a situation similar to a recession. The results were revealing. Under a no-modification model, which does not consider any adjustments to mortgage terms, the default rate increased by as much as 1.5 percentage points in response to these unexpected shocks. This research underscores the importance of loan modifications during times of economic distress, and its findings suggest that without such modifications, default rates tend to rise substantially, potentially exacerbating economic instability.

Foote et al. (2009) suggest that choosing loan modifications can yield substantial benefits for the broader economy. These estimates propose that opting for loan modifications, rather than proceeding with foreclosure, could potentially result in gains reaching a staggering \$180 billion, equivalent to more than 1% of the nation's gross domestic product (GDP). This perspective underscores the notion that loan modifications have the potential to be not only financially viable but also a significant contributor to overall economic health. However, they also offer an opposing viewpoint that challenges the magnitude of these gains, or even their existence, when viewed from the perspective of investors. This scepticism raises questions about whether the actual financial benefits of loan modifications are as substantial as

originally estimated. From this point of view, it is suggested that, although loan modifications may offer advantages for borrowers and the broader economy, they might not necessarily translate into substantial financial gains for investors.

In the topic of mortgage default, one crucial sub-concept comes into play: redefault. Redefault refers to the recurrence of delinquency or default after an initial period of nonpayment, often prompting foreclosure proceedings. A research study led by Haughwout et al. (2009), suggests that the likelihood of re-defaulting on mortgages decreases as the magnitude of the reduction in the monthly payment increases. Furthermore, the study reveals that this decrease in the re-default rate is more pronounced when the payment reduction is accomplished through the forgiveness of principal, as opposed to reducing interest rates. The Haughwout et al. (2009) study also found that delinquent borrowers who receive mortgage modifications frequently display a notable propensity to default. Specifically, their findings highlight the importance of borrower equity, or the interaction between the mortgage balance and the value of the home, in defining the outcome of these modifications, even though the primary goal of programmes like HAMP (Home Affordable Modification Programme) is to reduce payment loads. Mora (2012) found that mortgage modifications and redefault probabilities were influenced by market and credit risk dynamics similar to past financial crises. According to this study, credit risk, often not fully captured in market prices for less liquid assets, such as loan guarantees, played a significant role. Increased economic distress increased the likelihood of defaults, as seen in previous crises, where asset volatility and the inability of counterparties to meet obligations exacerbated the risks.

On another perspective, Quercia and Ding (2008) examine how different types of loan modification impact redefault rates. The findings indicate that greater reductions in mortgage payments lead to lower risk of default, contrary to common industry practices that often result in higher payments. Additionally, modifications that include principal forgiveness show the lowest redefault rates, as they address both payment affordability and negative equity. Although reducing repayment rates is crucial, the optimal solution must balance the interests of borrowers, investors, and other stakeholders. The study highlights the need for industry standards and tailor-made modifications based on borrower conditions and market factors. However, they note that further research is necessary to validate these findings across different periods and types of mortgage.

Loan modifications, initially perceived as ineffective due to high re-default rates during the 2007-2008 crisis, have shown significant improvement over time. Calem et al. (2018) studied modified loans between 2008 and 2011, revealing that modifications, especially those involving principal and payment reductions, performed better than self-curing loans. Improved economic conditions and servicer experience contributed to this success. They suggest that encouraging loan modifications was a beneficial public policy, although further research is needed to fully understand costs and benefits and optimize future policies.

Paul et al. (2018) focused on analysing the redefault rates of delinquent mortgage borrowers who received loan modifications compared to self-cured borrowers during the period 2008-2011 and found that the larger decline in the frequency of redefault of modified loans compared to self-cured loans was influenced by factors such as an increasing share of principal modifications, which tended to perform better than other types of modifications. On the other hand, Jian et al. (2018) found that modified mortgages have a higher re-default risk compared to never-defaulted loans, indicating the limitations of loan modification programmes in preventing foreclosures. Also, they point out that the redefault hazard for modified loans is less influenced by traditional risk factors than nonmodified loans, highlighting the need for tailored risk assessment models for modified mortgages.

2.2. HYPOTHESIS DEVELOPMENT

From a comprehensive review of the existing literature, it is evident that shock events consistently emerge as key factors influencing mortgage defaults. A significant number of studies and empirical analyses have converged on this finding, underscoring its importance in the domain of mortgage research. Given this prevailing consensus and due to a gap in existing literature, I am motivated to dive deeper into the repercussions of COVID-19 as a shock event on the mortgage landscape. Specifically, my objective is to examine the impact of COVID-19 on the probability subsequent to loan modifications.

Central to this investigation are two key hypotheses that seek to explore the nuances of these impacts.

H1: Mortgage modifications made post the onset of the COVID-19 pandemic have a lower redefault probability than those made prior.

This hypothesis posits that the mortgage modifications implemented after the onset of the COVID-19 pandemic have been more effective in preventing redefault compared to those made before the pandemic. The rationale behind this hypothesis is that unique economic conditions and extensive government interventions during the pandemic may have led to more favourable modification terms or better support mechanisms for borrowers. By examining the redefault probability of mortgages modified before and after the pandemic's onset, this study aims to determine whether the pandemic-driven modifications have indeed resulted in improved financial stability for homeowners.

H2: An external shock such as the COVID-19 pandemic caused changes in the main triggers to redefault.

This hypothesis suggests that the COVID-19 pandemic has altered the primary factors that lead to re-default on modified mortgages. By analysing data on the causes of redefault during the pandemic compared to prepandemic periods, this research aims to identify any significant changes in the underlying factors contributing to redefault.

3. METHODOLOGY

3.1. LOGISTIC REGRESSION

The primary objective of this thesis is to evaluate the effectiveness of loan modifications and to assess the impact of the COVID-19 pandemic on the success of these modifications, by analysing the redefault probability. To achieve this, we will employ two logistic regression models, one for each hypothesis. Logistic regression is a statistical method widely used in the field of predictive analytics and machine learning for binary classification tasks.

The fundamental tenet of logistic regression is the assumption of a latent, unobserved variable y^* that generates the observed binary outcomes $y = 0$ or $y = 1$. This undetected y^* can be represented by a linear equation since it is defined for the interval between $-\infty$ and $+\infty$.

$$(1) \quad y^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

However, since y^* is not observed, it needs to be connected to the dichotomous variable y that is observed in order for us to understand it. The assumption that $y = 1$ is observed once y^* surpasses a particular threshold provides this relationship.

$$(2) \quad P(Y = 1|X) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n}}$$

where:

- $P(Y = 1|X)$ is the probability that $Y = 1$ given a certain X .
- β_0 is the intercept.
- $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the predictors.
- X_1, X_2, \dots, X_n are the predictor variables.

As a result, logistic regression is non-linear in terms of probabilities but linear in terms of the latent dependent variable, y^* .

Equation (2) illustrates that the coefficients of logistic regression are defined by a linear model of the unobserved dependent variable. As a result, the interpretation of this unobserved result is identical to that of a linear regression: the intercept of the y axis, represented by the constant term β_0 , represents the expected value of y^* when X is 0. The coefficients β_i provide the slope of the regression line, signifying a change of β_i in y^* when x_i increases y^* by one unit while maintaining the other x constant. Consequently, a negative logit coefficient indicates that the independent variable has a negative impact on the underlying dependent variable y^* (the greater the x , the smaller the y^*), while a positive coefficient indicates that the independent variable has a positive impact (the larger x , the smaller the y^*).

Beyond just determining the direction of the effect, logit coefficient exponentiation provides a meaningful and comprehensible interpretation (also known as "odds ratios"). In fact, it is simple to rearrange Equation (2) to obtain:

$$(3) \quad \frac{P(Y = 1|X)}{1-P(Y = 1|X)} = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n} = e^{\beta_0} e^{\beta_1 x_1} e^{\beta_2 x_2} \dots e^{\beta_n x_n}$$

where $\frac{P(Y = 1|X)}{1-P(Y = 1|X)}$ is the odds of $Y=1$. As a result, the model becomes multiplicative instead of additive, and the interpretation of the coefficients ($exp(\beta)$ vs β) is significantly altered. First off, rather than indicating effects in the latent dependent variable y^* , $exp(\beta)$ reflects effects in the probabilities of $y = 1$. Second, the effect is multiplicative rather than additive. For instance, $exp(\beta_i) = 2$ implies that as x_i grows by one unit, the odds of $y = 1$ double (multiply by 2), and $exp(\beta_i) = 0.33$ suggests a two-thirds drop in the probabilities (multiply by 0.33). In general, a negative link between the two variables is indicated by $exp(\beta) < 1$ and a positive one by $exp(\beta) > 1$.

For more information on logistic regression models refer to Best, H., & Wolf, C. (Eds.). (2015), Harrell, F. E. (2015), Hosmer Jr et al. (2013).

Although other models such as Decision Trees, Random Forests, Gradient Boosting Machines, Support Vector Machines or Neural Networks could have been used (and should be explored in a future research), we selected the Logistic Regression model for the high interpretability of the outcome (through interpretation of p-values and coefficients) and reduced computational cost, when compared to these other approaches.

3.2. MODELS AND VARIABLES

In both models, the dependent variable is whether the borrower has redefaulted after the modification of the loan terms.

The first explanatory variable included in the model is the COVID dummy, which will equal one (1) when the modification of the loan was made after the COVID-19 pandemic shaken the global economic, which we assumed was January 2020, and zero (0) for modifications made before that. The type of modification is also used as explanatory variable. We will input two dummy variables regarding modifications. The first of them will be the modification to the loan terms and the second one with modifications regarding the interest rate. In addition to those, other variables will be used to predict whether or not the borrower will default (redefault), such as original loan characteristics, by adding the loan term and loan-to-value ratio, borrower characteristics- by adding credit score and debt-to-income, or property characteristics- by adding the type of property the loan regards to. All these variables take into account the effect of external factors on the outcome. To test the second hypothesis, we will include the interaction terms between COVID Dummy and the other key variables to assess how the effects of these variables on redefault probability differ pre and post COVID. Whether or not the new variables are statistically significant reveals how COVID-19 interacted

with each of those variables. The p-value and coefficient of each interaction term indicates whether the effect of X_i on redefault probability significantly changes when the dummy variable COVID changes. This means that variables that are statistically significant and have a positive coefficient have their effect amplified after the epidemic. Interaction variables that do not show statistical significance suggests that the relationship between predictor variables does not differ significantly across the levels of the variable in the study (in this case, whether or not the modification was made prior to the onset of the pandemic).

With that in mind, the following models will be tested:

$$(1) \quad \text{Redefault} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + e$$

$$(2) \quad \text{Redefault} = (1) + \sum \beta_n \text{COVID_Dummy} X_n$$

Table 1 is presented below with a list of the incorporated variables.

Table 1 - Variables Description

Variable	Description
Dependent Variable	
Redefaulted	Whether the borrower redefaulted after a modification (Yes = 1; No = 0)
Independent Variables	
COVID (Dummy) X_1	Whether the modification was made before or after the COVID-19 pandemic (Yes = 1; No = 0)
Modifications Type Variables	
Interest Rate Modification (Dummy) X_2	An indicator that denotes if the modification is regarding the interest rate (Yes = 1; No = 0)
Loan Term Modification (Dummy) X_3	An indicator that denotes if the modification is regarding the loan term (Yes = 1; No = 0)
Property Characteristics Variables	
Property Type SF (Dummy) X_4	An indicator that denotes if the property is a single-family home.
Loan Characteristics Variables	
Loan Purpose P X_5	An indicator that denotes if the mortgage loan is a purchase money mortgage (Yes = 1; No = 0)
Original Loan Term X_6	The number of months in which regularly scheduled borrower payments are due at the time the loan was originated

Original Loan-To-Value Ratio (LTV) X_7	The ratio, expressed as a percentage, obtained by dividing the amount of the loan at origination by the value of the property
Borrower Characteristics Variables	
Borrower Credit Score X_8	A numerical value used by the financial services industry to evaluate the quality of borrower's credit
Debt To Income X_9	The ratio obtained by dividing the total monthly debt expense by the total monthly income of the borrower at the time the loan was originated

Source: Author's preparation and Fannie Mae.

3.3. DATA AND SAMPLE SELECTION

In evaluating the effectiveness of loan modifications and assessing the impact of the COVID-19 pandemic on the success of these modifications, it is crucial to define the scope of the analysis.

In this thesis, the analysis is based on a subset of loan performance data provided by Fannie Mae, specifically targeting a deeper understanding of the credit performance of single-family mortgage loans. The data set used focusses on loans originated in the first two quarters of 2015 that follow through to the end of 2023 and is composed of 15345 loans. All these loans were modified throughout his lifecycle as we want to better understand how those modifications worked before and after the global epidemic. Another significant decision is to focus exclusively on loans that belong to homeowners. Homeowners typically share more homogeneous financial and demographic characteristics compared to nonhomeowners. This homogeneity can help reduce variability caused by differing borrower profiles, leading to more robust and interpretable results.

Analysing mortgage loan data originated in this year can provide valuable insights into the baseline conditions of the housing market and consumer borrowing behavior in a relatively stable economic period and allow one to understand how loans originated in pre-pandemic conditions behaved during these harsher periods.

To better analyse the economic context of this period, we need to separate it into pre-covid and post-covid. Between 2015 and 2019, the U.S. mortgage market experienced notable shifts influenced by both monetary policy and regulatory changes. In 2015, the Federal Reserve began the process of normalising monetary policy by raising the federal funds rate for the first time since 2006. This marked the beginning of a gradual series of rate hikes, with the federal funds rate increasing incrementally through 2018. The average mortgage rate during this period fluctuated but generally trended upward, rising from around 3.85% in 2015 to 4.54% in 2018 before falling to 3.94% in 2019 following a change in Fed policy.

In 2019, the Federal Reserve made a crucial decision to cut rates three times, reversing its previous position and significantly lowering the federal funds rate. This reduction in interest rates contributed to a decrease in mortgage rates, which, in turn, boosted housing affordability and stimulated borrowing and refinancing activities. The housing market saw increased demand, particularly among first-time home buyers and those purchasing lower priced homes. Although home prices continued to increase, the pace of growth moderated compared to the rapid increases observed in previous years. The period also saw significant regulatory changes. In 2015, the TILA-RESPA Integrated Disclosure (TRID) rule was implemented, improving the consumer's understanding of mortgage terms and improving transparency. Furthermore, discussions around the expiration of the Consumer Financial Protection Bureau (CFPB) Qualified Mortgage (QM) patch in 2019 raised concerns. The QM patch allowed certain loans to qualify as QMs even if the debt-to-income ratio exceeded the standard 43% threshold, provided they met other criteria and were eligible for purchase by Fannie Mae or Freddie Mac. Adjustments to the Home Mortgage Disclosure Act (HMDA) data collection and reporting requirements were also made, with the aim of achieving greater transparency in the way mortgage data was collected and reported by financial institutions. The unemployment rate continued to decrease during this period, reaching historically low levels of around 3.5% at the end of 2019. Inflation rates remained subdued and below the Federal Reserve target of 2%, which supported consumer confidence and spending, including on major purchases such as homes. In general, the combination of fluctuating interest rates, moderate economic growth, and regulatory adjustments provided a dynamic and supportive backdrop for the mortgage market from 2015 to 2019.

The period from 2020 to 2023 was characterised by unprecedented challenges and responses, significantly impacting the US mortgage market. The outbreak of the COVID-19 pandemic in early 2020 prompted swift and substantial actions from the Federal Reserve, including cutting the federal funds rate to near zero levels to support the economy. The average mortgage rate fell to historic lows, with rates around 3.11% in 2020, causing a surge in refinancing and home purchases as borrowers took advantage of the lower borrowing costs. These low mortgage rates helped offset the economic uncertainty caused by the pandemic, supporting housing affordability, and stimulating demand across various market segments. The Federal Reserve also implemented quantitative easing measures, purchasing large amounts of mortgage-backed securities to ensure liquidity in the mortgage market.

These actions, coupled with various fiscal stimulus packages, helped stabilise the economy and the housing market during the initial shock of the pandemic. As the economy began to recover in 2021, mortgage rates remained relatively low, but started to climb higher as inflation concerns grew. The average mortgage rate increased to around 3.45% in 2021 and continued to rise in subsequent years as the Federal Reserve signaled and eventually implemented rate hikes to combat rising inflation. By 2023, the average mortgage rate had risen to approximately 6.0%, reflecting the Fed's more aggressive stance on controlling inflation. Regulatory changes during this period also affected the mortgage landscape. The

expiration of the Consumer Financial Protection Bureau (CFPB) Qualified Mortgage (QM) patch in January 2021 led to new standards for qualifying loans, impacting lending practices and borrower eligibility. Despite the challenges posed by the pandemic, the housing market remained robust, with home prices continuing to increase, albeit at varying rates. Strong demand, coupled with low inventory, contributed to significant appreciation of home prices in many areas. The labour market showed resilience, with the unemployment rate gradually decreasing from pandemic-induced highs and inflation rates fluctuating, driven by supply chain disruptions and other economic factors. Overall, the period from 2020 to 2023 was marked by significant volatility and rapid changes in the mortgage market, driven by the Federal Reserve's monetary policy responses to the pandemic, economic recovery efforts, and ongoing regulatory adjustments. These factors collectively shaped the credit performance of US mortgage loans, providing a unique and complex landscape for analysis.

4. RESULTS

4.1. DESCRIPTIVE STATISTICS

Table 2 presents the descriptive statistics of the continuous variables of the total sample.

Table 2 - Descriptive statistics for continuous variables

		Original Interest Rate	Original UPB	Original Loan Term	Original Loan to Value Ratio LTV	Borrower Credit Score	Debt To Income
N	Valid	15646	15646	15646	15646	15646	15646
	Missing	0	0	0	0	0	0
Mean		4.282	224185.0	337.6	81.8	701.2	37.4
Median		4.250	204000.0	360.00	80.0	696.0	39.0
Std. Deviation		0.430	113656.8	58.4	12.6	47.5	7.1
Range		3.375	673000.0	276.0	57.0	350.0	48.0
Minimum		2.375	22000.0	84.0	40.0	479.0	2.0
Maximum		5.750	695000.0	360.0	97.0	829.0	50.0

Source: Author's preparation.

Table 3 presents the descriptive statistics of the categorical variables of the total sample.

Table 3 - Descriptive statistics for categorical variables

		Frequency	Percent	Valid Percent	Cum. Percent
Covid Dummy	0	9514	60.8	60.8	60.8
	1	6132	39.2	39.2	100.0
	Total	15646	100.0	100.0	
Interest Modification Dummy	0	6239	39.9	39.9	39.9
	1	9407	60.1	60.1	100.0
	Total	15646	100.0	100.0	
Loan Term Modification Dummy	0	411	2.6	2.6	2.6
	1	15235	97.4	97.4	100.0
	Total	15646	100.0	100.0	
Loan Purpose P	0	6934	44.3	44.3	44.3
	1	8712	55.7	55.7	100.0
	Total	15646	100.0	100.0	
Property Type SF	0	6036	38.6	38.6	38.6
	1	9610	61.4	61.4	100.0
	Total	15646	100.0	100.0	

Source: Author's preparation.

Borrowers in this population had an average interest rate of 4.278%, with the majority of loans clustering around the median rate of 4.250%. Borrower credit scores averaged 701.022, with a median score of 695. This indicates a generally creditworthy population, though scores ranged from 479 to 829, encompassing a wide spectrum from fair to excellent credit profiles, since credit score valuation ranges from 300 to 850 and a good credit score is normally in the region of 700. The interest rates were fairly consistent, ranging from a low of 2.375% to a high of 5.750%, indicating a stable lending environment with limited fluctuation.

The average original unpaid principal balance (UPB) for these loans was \$223,399.46, with a median value of \$203,000.00. This suggests that most borrowers took out loans around this median amount, although the UPB ranged widely from \$20,000 to \$1,200,000. This wide range reflects a diverse borrower base, with some taking out relatively small loans while others secured significantly larger amounts. The loan terms within this population averaged 336.80 months, which is approximately 28 years, with a median term of 360 months (30 years). While almost all (86,6%) borrowers opted for the traditional 30-year mortgage, some shorter-term loans were also present, as indicated by the minimum term of 84 months (7 years).

Loan-to-value (LTV) ratios in this population had an average of 81.067% and a median of 80%. The ratios ranged from as low as 10% to as high as 97%, suggesting that while most borrowers financed a substantial portion of their property value through loans, there were also instances of both very low and very high leverage. The debt-to-income (DTI) ratios averaged 37.400%, with a median of 39%. This suggests that a significant portion of borrowers' income was devoted to debt repayment. The DTI ratios varied from as low as 2% to a maximum of 50%, reflecting diverse financial situations among the borrowers.

Furthermore, the appendix tables 4 and 5 were created with only the loans that were modified pre and post COVID for the continuous variables, respectively. They show no major differences in the populations, as it is to be expected since loans were originated in the same period.

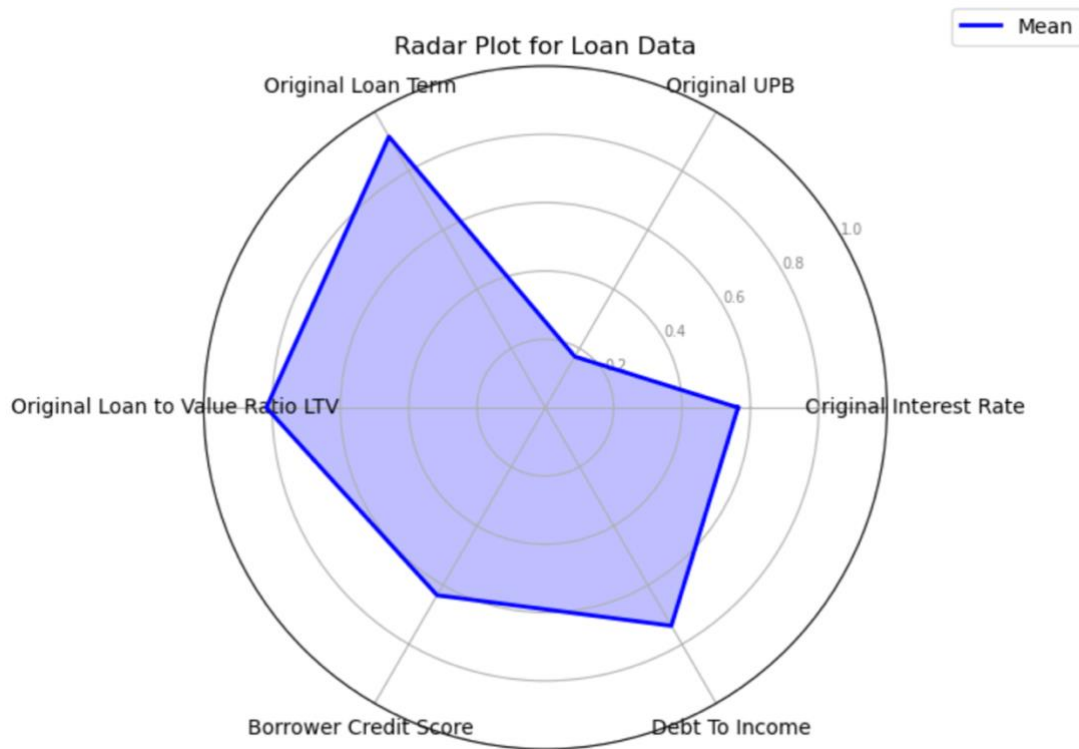


Figure 1 - Radar Plot of the Mean Original Loan and Borrower Characteristics

4.2. REGRESSION RESULTS AND POLICY IMPLICATIONS DISCUSSION

As mentioned in the previous chapters, the analysis starts with a logistic regression relating the probability of re-default after modification, which will be followed by another logistic regression addressing the main triggers to re-default. The results in Table 4 below demonstrate a significant relationship between the dependent variable and several independent variables, including the COVID dummy variable.

With a negative coefficient and the highest z score, the COVID Dummy is highly significant. This indicates that in the post-COVID period there is a significantly lower likelihood of redefaulting following modification. The fact that the modification was made after the onset of COVID-19 decreases the probability of redefaulting by 27% ($\exp(-1.3102) * 100$). Other interesting results show that loans that had a modification to the interest rate are less likely to re-default than those that had a modification to the loan terms, with a modification to these latter enhancing the probability of default (as seen by the positive coefficient).

For the debt-to-income variable, we have a positive coefficient that reveals the higher the individual's degree of leverage of the individual, the higher the likelihood of defaulting. Actually, an increase in 10% of the debt-to-income variable, that is in percentage, increases the probability of redefaulting in 9% ($\exp(10 * 0.0088) * 100$). Debt-to-Income is widely seen as a financial stress indicator, so it is not surprising that the most pressured debtors are – according to the results – more redefault-orientated. In addition to this, the loan-to-values

explanatory variable presented a similar result to the one previously observed, showing a higher likelihood of redefault in higher loan-to-value mortgages. This can be explained by the fact that lower LTV loans are usually contacted by wealthier individuals, who are usually in a less financially stressed position.

Looking at the remaining explanatory variables, single-family houses' mortgages also presented significant results and a positive coefficient, which means that the probability of default is higher in this group of households. This result can be seen as expected, since this segment of housing is generally less affordable, meaning that families have to put in extra effort to keep up with their mortgage payments.

Table 4 - Model Results for H1

Variables	Coef.	std err	z	P> z 	[0.025]	[0.975]
const	1.5991	0.339	4.723	0.000	0.936	2.263
COVID Dummy	-1.3102	0.039	-33.331	0.000***	-1.387	-1.233
Interest Rate Modification	-0.3502	0.037	-9.405	0.000***	-0.423	-0.277
Loan Term Modification	0.4471	0.132	3.383	0.001**	0.188	0.706
Loan Purpose P	0.1940	0.045	4.273	0.000***	0.105	0.283
Property Type SF	0.1039	0.037	2.831	0.005**	0.032	0.176
Original Loan Term	0.0030	0.000	8.663	0.000***	0.002	0.004
Original LTV	0.0060	0.002	3.352	0.001**	0.002	0.009
Borrower Credit Score	-0.0055	0.000	-14.226	0.000***	-0.006	-0.005
Debt-To-Income	0.0088	0.003	3.422	0.001**	0.004	0.014

Notes: ***, **, *, † respectively represent significance levels below 0,1%, 1%, 5% and 10%.

Furthermore, it is possible to observe in appendix A that the model is statistically significant. Although a pseudo-R squared of 0.08592 suggests that the model has a modest level of explanatory power, a p-value of 0.000 in the Likelihood Ratio (LR) test (which tests the null hypothesis that all coefficients of the model are equal to zero) strongly rejects the null hypothesis, indicating that the model is statistically significant. Also, the appendix B is a ROC curve plot that shows us a value of 0.7 which tells us that the model has a fair to good performance

The findings suggest that crisis-specific interventions can be highly effective. Policymakers should consider maintaining or even expanding these types of intervention during future

economic downturns or crises. This could include more flexible modification terms, temporary forbearance, and customised support programmes for borrowers facing financial hardships.

The finding that interest rate modifications are more effective in reducing the likelihood of redefault compared to loan term modifications highlights the importance of focussing on interest rate adjustments as a primary strategy for loan modifications. Policymakers and financial institutions should prioritise interest rate reductions over loan term extensions when designing modification programmes, as these appear to provide greater stability for borrowers.

The varying effectiveness of different types of modification (interest rate vs. loan terms) underscores the need for customised modification strategies. For this to happen, collaboration between government agencies, financial institutions, and community organisations is essential. Policymakers should encourage lenders to assess individual borrower situations more closely and tailor modifications to meet their specific needs, rather than applying a one-size-fits-all approach. Also, there should be increased efforts to educate borrowers about the availability and benefits of loan modifications, especially during economic crises.

Outreach programmes can ensure that borrowers are aware of their options and can take advantage of modification programmes before they reach the point of default. By creating a supportive regulatory environment, policymakers can improve the effectiveness of modification programmes. Continuous monitoring and evaluation of modification programmes could be another measure to prevent borrowers from taking the wrong path once again. Policymakers should invest in systems to track the performance of modified loans over time and adjust policies based on data-driven insights. This ensures that the most effective strategies are identified and scaled up, while less effective ones are reformed or discarded.

Given the success of post-COVID mortgage modifications, there is a strong case for implementing well-designed and proactive intervention programs that can lead to long-term financial stability for borrowers even outside of crisis periods. Policymakers could encourage lenders to offer modifications to borrowers who show early signs of financial distress. This could prevent defaults and stabilise the housing market.

To evaluate whether or not the main triggers to re-default change when the modifications are made prior and after the COVID-19 outbreak, we introduce the interaction terms of the COVID dummy and the other explanatory variables. We then analyse the main effect coefficient and the interaction term coefficient, as they explain the effect of the variable in the absence of COVID-19 and the additional or different effect of the variable during the COVID period, respectively.

The results in Table 5 show that for the interest rate modification and loan term modification variables, both the main and interaction terms are significant. For the interest rate modification variable, we have a coefficient of -0,3955 for the main effect and a coefficient of 0,2673 for the interaction effect, which leads to a combined effect during covid of: $-0,3955 + 0,2673 = -0,1282$. This suggests that the effectiveness of interest rate modifications in reducing the likelihood of redefault is diminished during the COVID period, although it maintains the negative coefficient. The fact that the effectiveness of this modification in the success of the loan is lower in periods of economic crisis suggests that additional or alternative measures may be necessary to support borrowers more effectively.

Table 5 - Model Results for H2

Variables	Coef.	std err	z	P> z	[0.025]	[0.975]
const	1.2771	0.482	2.651	0.008	0.333	2.222
COVID Dummy	-0.5050	0.859	-0.588	0.557	-2.189	1.179
Interest Rate Modification	-0.3955	0.054	-7.371	0.000***	-0.501	-0.290
Loan Term Modification	0.9019	0.208	4.331	0.000***	0.494	1.310
Loan Purpose P	0.1757	0.064	2.766	0.006**	0.051	0.300
Property Type SF	0.1123	0.051	2.212	0.027*	0.013	0.212
Original Loan Term	0.0036	0.000	7.558	0.000***	0.003	0.004
Original LTV	0.0075	0.002	2.988	0.003**	0.003	0.012
Borrower Credit Score	-0.0065	0.001	-11.85	0.000***	-0.008	-0.005
Debt-To-Income	0.0147	0.004	4.053	0.000***	0.008	0.022
COVID Dummy: Interest Rate Modification	0.2673	0.092	2.918	0.004**	0.088	0.447
COVID Dummy: Loan Term Modification	-1.5181	0.309	-4.906	0.000***	-2.125	-0.912
COVID Dummy: Loan Purpose P	-0.0032	0.113	-0.028	0.977	-0.224	0.218
COVID Dummy: Property Type SF	-0.0883	0.092	-0.955	0.340	-0.270	0.093
COVID Dummy: Original Loan Term	-0.0013	0.001	-1.445	0.148	-0.003	0.000
COVID Dummy: Original LTV	-0.0003	0.004	-0.062	0.950	-0.009	0.008
COVID Dummy: Borrower Credit Score	0.0025	0.001	2.550	0.011*	0.001	0.004
COVID Dummy: Debt-To-Income	-0.0163	0.006	-2.601	0.009**	-0.029	-0.004

Notes: ***, **, *, † respectively represent significance levels below 0,1%, 1%, 5% and 10%.

For the variable of modification of the loan term, we have a coefficient of 0,9019 for the main effect and a coefficient of -1.5181 for the interaction effect, which leads to a combined effect during COVID of: $0.9019 - 1.5181 = -0.6162$. This indicates that, contrary to the intended effect, loan term modifications were associated with a higher probability of loan redefault before COVID-19. This might suggest that borrowers who were granted loan term modifications were already at a higher risk of redefaulting or that extending the loan term did not alleviate financial stress adequately. During the COVID period, the effect of loan term modification on the logarithmic odds of redefaulting changes by an additional -1.5181. This negative coefficient indicates that the relationship between loan term modification and redefaulting flips during COVID-19, with the modifications becoming more effective in reducing redefault risk, as shown by the combined effect coefficient. However, the fact that the confidence intervals report a difference greater than 1,00, shows us that there may not be a significant difference in the population (Stoltzfus, J. C., 2011), which is supported by the analysis of the data.

The borrower credit score and the debt-to-income maintain their importance and are both influenced by the covid factor, although their p-value may suggest that their significance is not as high as it was for the main effect. For the borrower credit score variable, we have a coefficient of $-0,0065$ for the main effect, with borrowers who have higher credit score being less likely to re-default, as expected, and a coefficient of $0,0025$ for the interaction term effect. This suggests that although COVID-19 pandemic increased the chances of a borrower with a fixed credit score to redefault, it is still a very good indicator that he most likely will not, as shown by the combined effect coefficient ($-0,0065 + 0,0025 = -0.0040$, which remains negative. For the debt-to-income variable, we have a coefficient for the main effect of $0,0147$. As for the interaction term, the coefficient is $-0,0163$, which suggests that the effect of covid in this variable is highly significant, as is shown by the flip in its relationship with the redefaulting event. A combined effect of -0.0016 ($0,0147 - 0,0163$) suggests that, during COVID, a higher debt-to-income actually reduces the probability of redefault. This may be due to beneficial programs created by the US government to help relieve the burden on the more indebted borrowers.

The variables originated by interacting loan purpose P, Property Type SF, original loan Term and Original Loan to value ratio with the COVID dummy, became not statistically significant in the model with the interaction terms, suggesting no substantial interaction effect with the COVID dummy variable.

Furthermore, it is possible to observe in Appendix C that the model is statistically significant. Although a pseudo R-square of 0.0876 suggests that the model has a modest level of explanatory power, a p-value of 0.000 in the Likelihood Ratio (LR) test (which tests the null hypothesis that all coefficients of the model are equal to zero) strongly rejects the null hypothesis. . Also, the Appendix D is a ROC curve plot that shows us a value of 0.7 which tells us that the model has a fair to good performance.

The analysis suggests that COVID had some implications on the main triggers for rescheduling, especially with regard to its weight in the chances the event of redefault has to occur. Also, the change in effects on the debt-to-income variable seems to suggest that this specific variable was greatly affected by the COVID-19 situation, and all the other remaining explanatory factors that remained also floated during the pandemic season. The abrupt change in individual wealth and well-being caused by the exogenous shock was transversal throughout the world, with the change in results reflecting the impact in the American citizens.

Although the most important variables used in this analysis (type of modifications and borrower credit score) are still the main influencers of the probability of default, some of the studied variables lost their significance when the interaction effect with COVID-19 is inserted into the equation, which suggests that some of the triggers were affected by this global epidemic.

5. DISCUSSION AND CONCLUSION

Our analysis revealed several key findings. First, the probability that a borrower who took a loan after the onset of the pandemic redefaulting on his mortgage loan decreased by 27%, compared to borrowers who took the loan before. Although it may seem contradictory, it actually suggests that programmes created by the US government during this harsh period were effective in helping borrowers stay afloat on their payments. The logistic regression models applied to data from Fannie Mae also yielded other results: borrower characteristics, such as debt-to-income ratio and credit score, were significant predictors of redefault probabilities, which goes accordingly with previous studies made by Chu and Park (2008) and Haughwout et al. (2008), respectively. Furthermore, we detected that the modifications involving changes in the interest rate were more effective in reducing re-default rates compared to those that were adjusting payment schedules. Furthermore, we found that the COVID-19 pandemic had a significant impact on the triggers to default, as is shown by the flip in the coefficient of the debt-to-income variable when comparing the main effect and compounding effect. These findings suggest that a higher debt-to-income ratio before COVID-19 increased the likelihood of rescheduling, while after the pandemic it actually decreased the chances of the rescheduling event. Once again, this may seem like an unexpected outcome, but shows the effort that was put into practice by the US government in the creation of effective programmes to help relief the burden on borrowers, especially the ones with higher leverage of debt to income.

The finding that loans altered after COVID-19 had a lower probability of redefault is supported by the programmes established by the US government. Programmes like the CARES Act, which is a \$2.2 trillion economic stimulus bill passed by the US government with over \$500 billion in direct payments to Americans that also included provisions for mortgage forbearance, allowing borrowers with federally backed loans to temporarily suspend payments without facing penalties or negative impacts on their credit scores, or the HAF, which provided states with funds to help homeowners struggling with their payments due to COVID-19, are likely the reason to explain why the probability to redefault lowered in such an anticlimatic environment. Also, for less struggling homeowners, there was a tendency to grow savings, as there was less incentive to spend on non-essential items and travel. This means that relief programmes were probably efficient in targeting struggling borrowers in a complicated period and could be replicated not only in harsh periods but also when the borrower shows early signs of mortgage default.

This study has limitations. For example, the loans studied in this paper were originated before COVID-19 and do not explain how the loans originated in the aftermath of the pandemic performed, focussing only on the comparison between loans that were modified before and after the strike of the global epidemic. Furthermore, the data used lack

information about the macroeconomic environment at the time of the origination of the contract, which could help improve the performance of the models.

Therefore, we recommend that future research on this topic explores the long-term effects of COVID-19-induced mortgage modifications on both borrowers and financial institutions, as there was shown that there is an impact, but was not quantified. Furthermore, studies that investigate the interaction between different types of loan modification and various economic scenarios to better predict their effectiveness in future crises. An additional study on time to redefault after the modification could also be interesting and could, in this case, put into greater perspective the impact COVID-19 had on the success of the mortgage modifications.

This thesis helped uncover the impact of the COVID-19 pandemic on mortgage modification practices and the probability of default, providing critical insights into the dynamics of mortgage defaults and the effectiveness of loan modifications during a period of unprecedented economic upheaval.

With this in mind, I conclude that shock events, such as the COVID-19 pandemic and all associated consequences, significantly contribute to change the way borrowers interact with their mortgage payments.

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APPENDIX A

Table A - Descriptive statistics for continuous variables when COVID Dummy = 1

		Original Interest Rate	Original UPB	Original Loan Term	Original Loan to Value Ratio LTV	Borrower Credit Score	Debt To Income
N	Valid	6023	6023	6023	6023	6023	6023
	Missing	0	0	0	0	0	0
Mean		4.236	232458.6	338.7	81.3	708.3	37.1
Median		4.250	212000.0	360.0	80.0	703.0	39.0
Std. Deviation		0.433	120913.7	57.1	12.6	48.0	7.3
Range		3.125	671000.0	264.0	57.0	294.0	46.0
Minium		2.500	24000.0	96.0	40.0	535.0	4.0
Maximum		5.625	695000.0	360.0	97.0	829.0	50.0

Source: Author's preparation.

Table B - Descriptive statistics for continuous variables when COVID Dummy = 0

		Original Interest Rate	Original UPB	Original Loan Term	Original Loan to Value Ratio LTV	Borrower Credit Score	Debt To Income
N	Valid	9322	9322	9322	9322	9322	9322
	Missing	0	0	0	0	0	0
Mean		4.311	218839.4	336.8	82.1	696.7	37.1
Median		4.375	200000.0	360.0	80.0	690.0	39.0
Std. Deviation		0.425	108382.0	59.2	12.5	46.6	7.3
Range		3.375	604000.0	276.0	57.0	346.6	46.0
Minium		2.375	22000.0	84.0	40.0	479.0	4.0
Maximum		5.750	626000.0	360.0	97.0	825.0	50.0

Source: Author's preparation.

Logit Regression Results

Dep. Variable:	Redefaulted after Modification	No. Observations:	15345
Model:	Logit	Df Residuals:	15335
Method:	MLE	Df Model:	9
Date:	Mon, 01 Jul 2024	Pseudo R-squ.:	0.08592
Time:	15:51:40	Log-Likelihood:	-9330.0
converged:	True	LL-Null:	-10207.
Covariance Type:	nonrobust	LLR p-value:	0.000

Figure A - Metrics of the model for H1

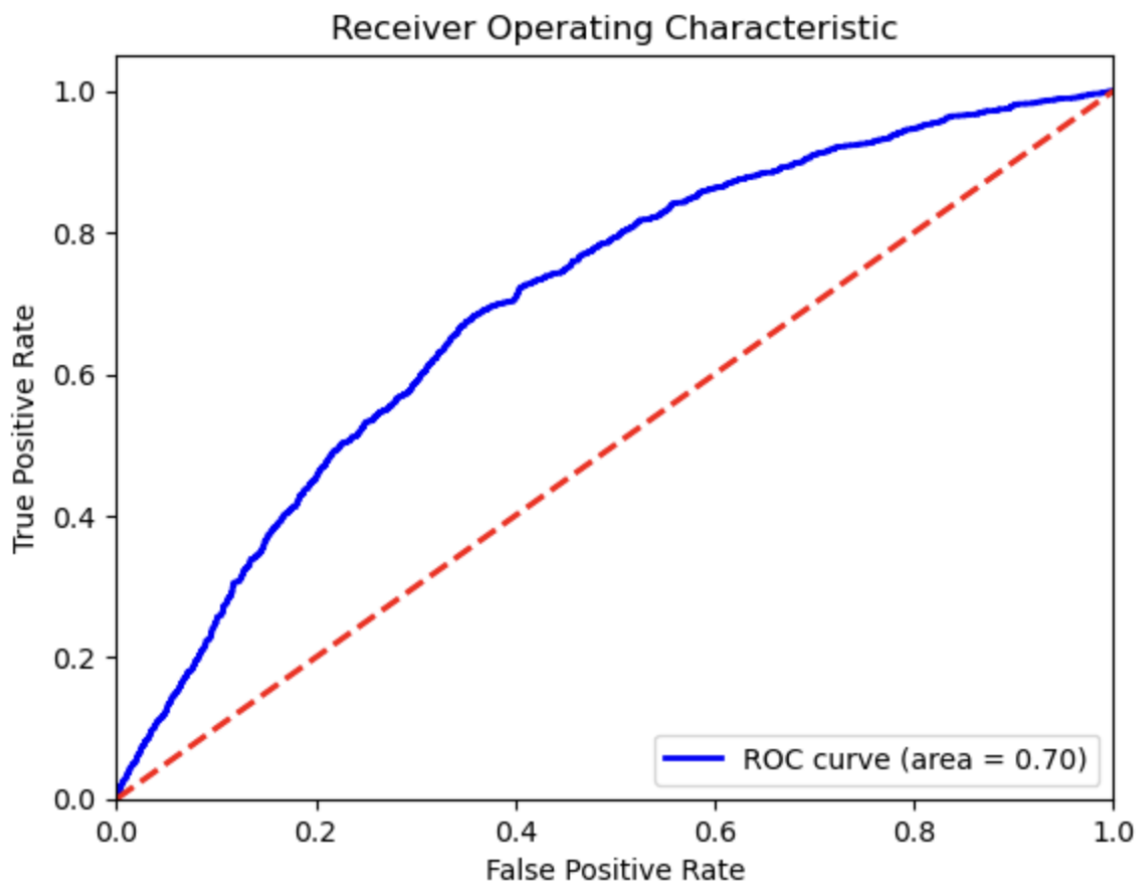


Figure B - ROC Curve for Model H1

Logit Regression Results

Dep. Variable:	Redefaulted after Modification	No. Observations:	15345
Model:	Logit	Df Residuals:	15328
Method:	MLE	Df Model:	16
Date:	Wed, 03 Jul 2024	Pseudo R-squ.:	0.08776
Time:	23:10:04	Log-Likelihood:	-9311.2
converged:	True	LL-Null:	-10207.
Covariance Type:	nonrobust	LLR p-value:	0.000

Figure C – Metrics of the model for H2

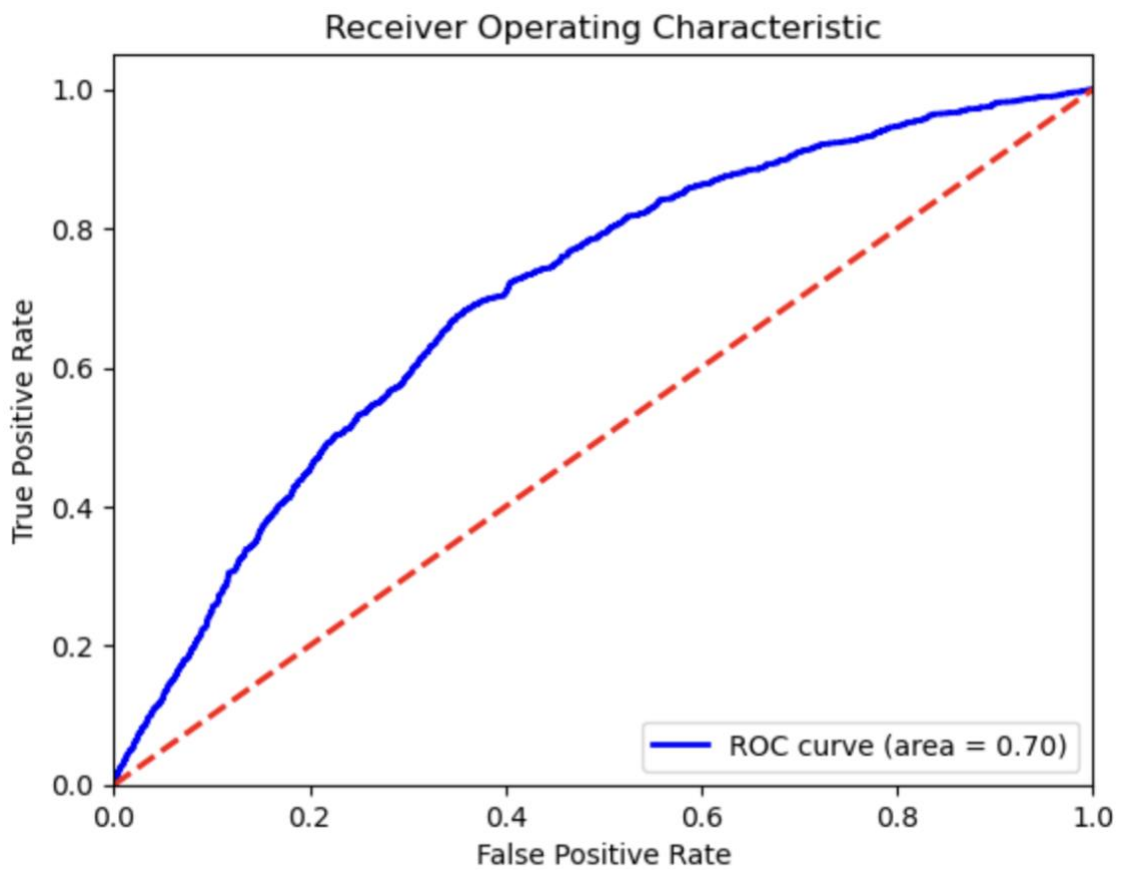


Figure D - ROC Curve for Model H2

