MILLIMAN WHITE PAPER

Assessing the Effectiveness of Payment Reduction on Preventing Borrower Re-default for Mortgages

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I: Introduction

The monthly processing of mortgage payments and related cash flows (e.g., the accrual of a borrower's escrow account) are managed by a mortgage servicer. The servicer can be the original bank, an independent mortgage bank, or a sub-servicer. Mortgage servicers are responsible for collecting and transmitting payments related to the mortgage. In addition, mortgage servicers are responsible for working with borrowers during financial hardship. This includes various loss mitigation activities and, in the event the borrower is unable to repay their mortgage, foreclosure or other types of disposition.

Loss mitigation refers to various options provided to borrowers experiencing financial hardship that are designed to facilitate home retention in lieu of the loss of the home for the borrower. Strategies often follow a loss mitigation waterfall that is outlined by the mortgage guarantor (e.g., Freddie Mac, Fannie Mae, the Federal Housing Administration, the Department of Veterans Affairs, or the bank if the loan is not sold to the secondary markets). The loss mitigation waterfall often involves some mixture of deferring the delinquent payments to the end of the mortgage or altering the amount of the monthly payment. The amount of loss mitigation is generally a function of the debt and income conditions of the borrower at the time of delinquency, and the types of loss mitigation offered to borrowers has varied across calendar periods. Upon successful completion of a loss mitigation strategy, the delinquent status of the borrower is typically reset to current, and the borrower can continue living in their home should the loss mitigation activity allow them to continue to make monthly payments.

This research seeks to understand the extent to which differences in payment reduction affect borrower outcomes following loss mitigation, without segmentation by the type of loss mitigation. More specifically, how does the size of the payment reduction affect the probability that a borrower will re-default? To do so, performance history on conventional loans modified between 2008 and 2012 is collected and re-default rates are compared across payment reduction bands to identify any trend visible in the data. Several regressions are also estimated to isolate the effects of the payment reduction from any confounding factors. The data used for this analysis is limited to data published by Freddie Mac and Fannie Mae.

Results indicate that larger payment reductions are generally correlated with lower rates of re-default. Model estimates indicate that a 1 percentage point decrease in the monthly payment corresponds to a 0.05 percentage point reduction in the probability of default, all else equal. Borrowers who receive no payment reduction perform consistent with those who receive an increased monthly payment following loss mitigation. These results indicate that payment reduction is a significant aspect of effective loss mitigation. Among borrowers who re-default, a significant portion do so within 6 months of receiving loss mitigation. Heterogeneity can be observed within the lowest credit score and income borrowers, as well as for loans that receive loss mitigation early.

II: Data & methods

The analysis uses Freddie Mac[1]and Fannie Mae's[2] public loan level performance datasets. The data was downloaded as of Q2 2023 and represents performance months through December 2022. The full data contains performance on 105 million distinct loans, 12 million of which were ever delinquent (indicated as ever missing a monthly payment). To receive loss mitigation, a borrower must be delinquent on their current mortgage or otherwise demonstrate financial hardship. Finally, we narrow the scope to purchase, fixed rate mortgages that received loss mitigation between 2008 and 2012, resulting in 99,551 loans. We focus on fixed rate mortgages because they comprise a vast majority of loans and they facilitate constant comparisons between monthly payments.

We focus on modifications that occurred between 2008 and 2012 for several reasons: Loss mitigation received increased attention relative to previous time periods due to fallout from the Great Recession, several alternative loss mitigation options were available, and this provides a sufficiently large performance history to date. Borrower re-default is measured as whether or not a loan has 6 or more cumulative missed payments following modification. Given limitations in tracking loss mitigation events in the data, outcomes for serial modification[3] are not closely studied. Loan performance is observed up to 2020 to avoid cross contamination with pandemic-related effects and policy. The final dataset represents monthly performance on these loans from 2008 to 2019, consisting of roughly 3 million records.

Payment reduction is calculated as the monthly payment after payment reduction divided by the monthly payment before. The monthly payment only includes principal and interest (P&I); we do not include taxes or insurance. For example, if the borrower's monthly P&I payment before loss mitigation was $1,000, and the payment was $750 after loss mitigation, the payment reduction would be calculated as 25% (750/1,000 – 1). Not all borrowers receive a payment adjustment from loss mitigation, and in some occurrences the monthly payment may increase. The effect of the payment reduction is then measured on re-default, which is defined as 6 months of cumulative missed payments or a foreclosure event occurring after loss mitigation.

Marginal and cumulative default rates are measured over time to evaluate re-default rates as a function of the change in the monthly payment. Statistical modeling is used to isolate the incremental effect of payment reduction from other related variables. This comes in the form of a linear probability model, which controls for borrower characteristics, loan characteristics, and economic conditions. Variables are added incrementally to observe changes in the point estimate for payment reduction. In the final model, a random effects structure is implemented to account for individual specific unobservable effects associated with default performance that would bias estimates of uncertainty. It may be that the individual specific effect is correlated with the amount of payment reduction, as well as the probability of re-default. In this case, a correlated random effects model may be more appropriate, though its computational complexity to implement is beyond the scope of this paper.

Finally, heterogeneity of default rates across segments of the sample with respect to payment reduction are explored to determine if the benefit (reduction in default probability) is equally distributed. These differences are measured by descriptive methods and qualified by statistical modeling where applicable.

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[1] Freddie Mac. (2023). Single family loan-level dataset. Retrieved September 16, 2023, from https://www.freddiemac.com/research/datasets/sf-loanlevel-dataset.

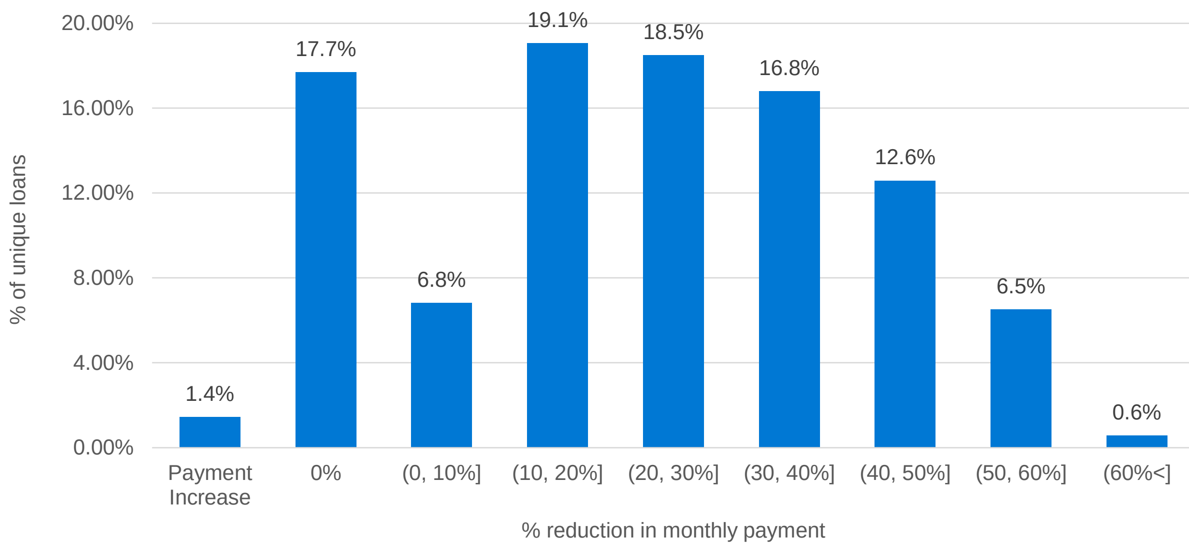
[2] Fannie Mae. (2023). Fannie Mae single-family loan performance data. Retrieved September 16, 2023, from https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-transfer/fannie-mae-single-family-loan-performance-data.

[3] Serial modification is internally defined as two or more modifications associated with the same loan.

III: Analysis

The first step of the analysis is to evaluate the relationships in the data. Figure 1 provides a distribution of unique loans relative to the amount of payment reduction provided by loss mitigation (any type):

FIGURE 1: LOAN COUNT BY PAYMENT REDUCTION AMOUNT (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY)



Most observations in the sample receive some form of payment reduction, though roughly 19% of loans do not receive a payment reduction. Approximately 1.4% of the loans experience an increase in their monthly payment. Many loss mitigation episodes during this period are loan modifications. For a loan modification, the servicer resets the mortgage rate to the current rate and extends the term of the mortgage out typically to 30 years (or give or take, depending on the program). Prior delinquencies and experiences are capitalized onto the modified mortgage. Therefore, if the new mortgage rate is greater than the existing mortgage rate or if the capitalized amount is sufficiently large, the result can be a payment increase. The loan modification could be approved because the borrower may be able to repay the higher mortgage amount but may have been unable to make up prior missed payments.

Most borrowers in the dataset received somewhere between a 10% and 30% payment reduction after loss mitigation. Reductions appear to drop off above 60% in the sample, with a very small portion making up this group. Most of the individuals on the upper end of the payment reduction distribution receive a payment reduction later in the life of the mortgage relative to other loans. While the average loan age at the time of loss mitigation hovers around 4-5 years for many of the payment reduction cohorts, those who receive greater than a 60% reduction in their monthly payment have an average loan age of 7.5 years. The loan is often re-amortized to a new term upon modification, therefore loans with a greater amount of the principal paid off at this time will inherently see a steeper reduction in their payment.

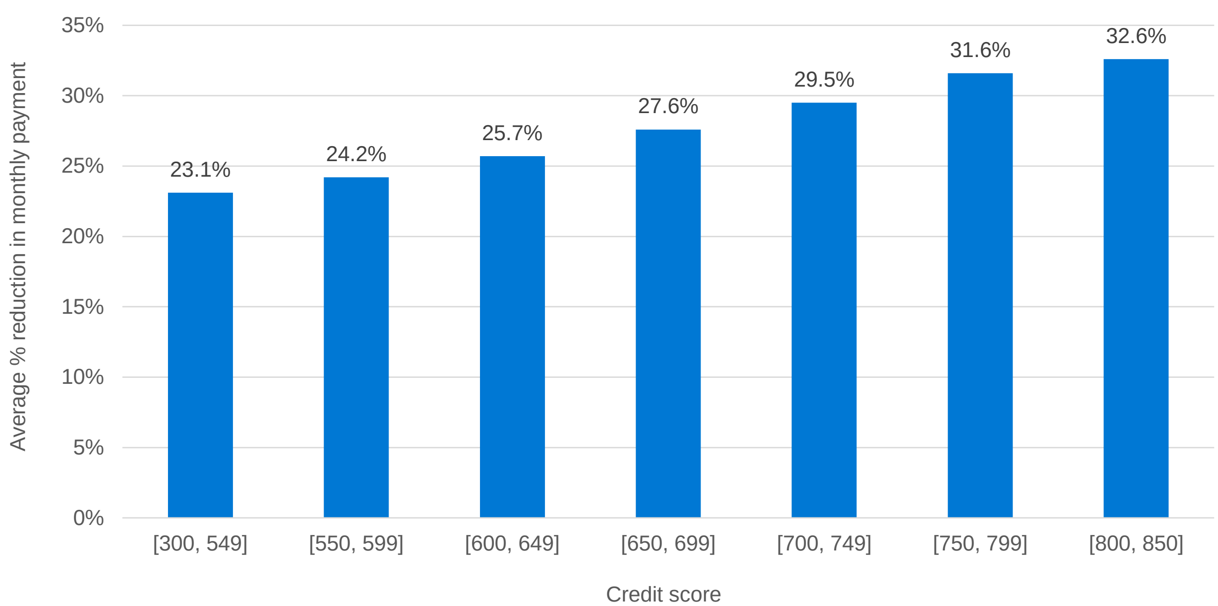
Figure 2 provides a summary of borrower and loan characteristics by payment reduction cohort.

FIGURE 2: WITHIN SAMPLE AVERAGE LOAN CHARACTERISTICS BY PAYMENT REDUCTION COHORT

PAYMENT REDUCTION	N	CREDIT SCORE	LOAN TO VALUE	DEBT TO INCOME	FIRST TIME HOME BUYER (%)	ORIGINAL INTEREST RATE	AGE AT MODIFICATION (MONTHS)
Payment increase	1384	667	83.1%	41.2%	37.2%	6.40%	54.3
0%	16995	668	85.0%	40.3%	31.9%	6.31%	56.7
(0, 10%]	6556	680	84.8%	42.8%	34.6%	6.32%	51.7
(10, 20%]	18309	681	86.1%	43.1%	34.7%	6.35%	50.7
(20, 30%]	17768	688	85.5%	43.1%	34.2%	6.25%	58.5
(30, 40%]	16137	693	85.0%	43.5%	34.7%	6.26%	57.9
(40, 50%]	12096	695	84.8%	43.9%	35.8%	6.35%	56.9
(50, 60%]	6264	695	84.4%	43.6%	39.6%	6.35%	61.1
(60%<]	554	689	81.6%	39.4%	31.8%	6.43%	93.0

There are moderate differences across traditional risk characteristics, but these are not extreme. The sample is already relatively homogenous given that all loans needed to have been delinquent prior to receiving loss mitigation. Loans that received greater than a 60% reduction tended to be about 30 months older on average, though this is a small group of borrowers and other payment groups have average ages around 50 to 60 months. There are some notable differences within credit score, where borrowers receiving a payment increase or no change in the monthly payment tend to have lower scores, on average. The relationship between credit score and loss mitigation is examined more closely in Figure 3:

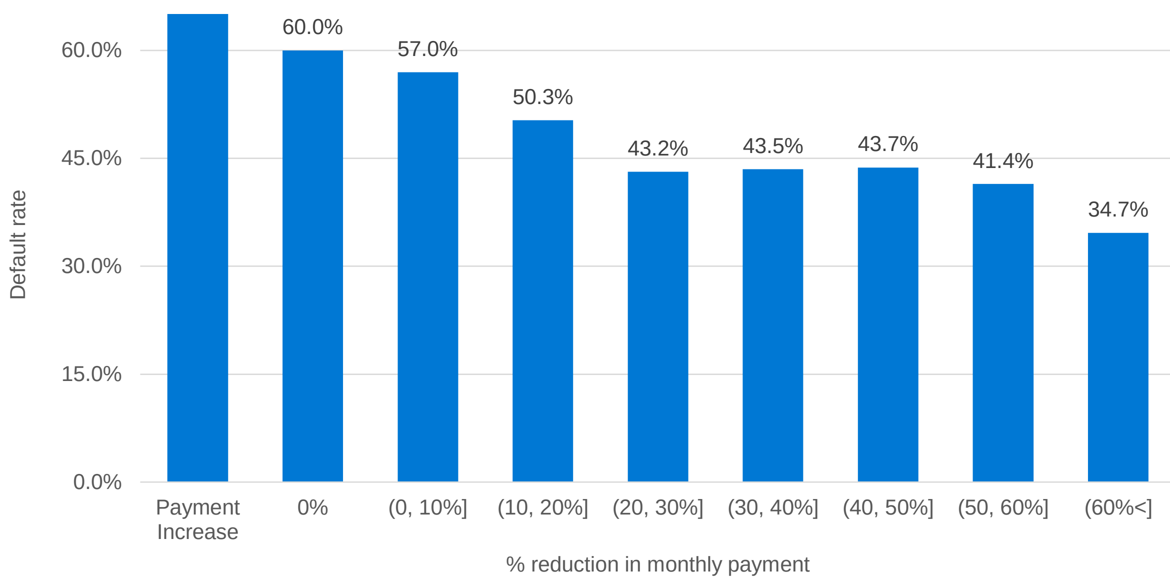
FIGURE 3: PAYMENT REDUCTION BY CREDIT SCORE (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY)



In the historical data, there is a positive relationship between the borrower's original credit score and the amount of payment reduction. This is especially curious given that borrowers with stronger credit tend to have lower starting interest rates and the average age at the time of modification is negatively correlated with credit score in the sample. It may be that borrowers with lower credit scores are more likely to default during stronger economic cycles (typically marked by higher interest rates used to curb inflation) relative to higher credit borrowers, leading to less of a payment reduction, though definitive evidence of this is beyond the scope of this paper.

The re-default rate by payment reduction is displayed in Figure 4:

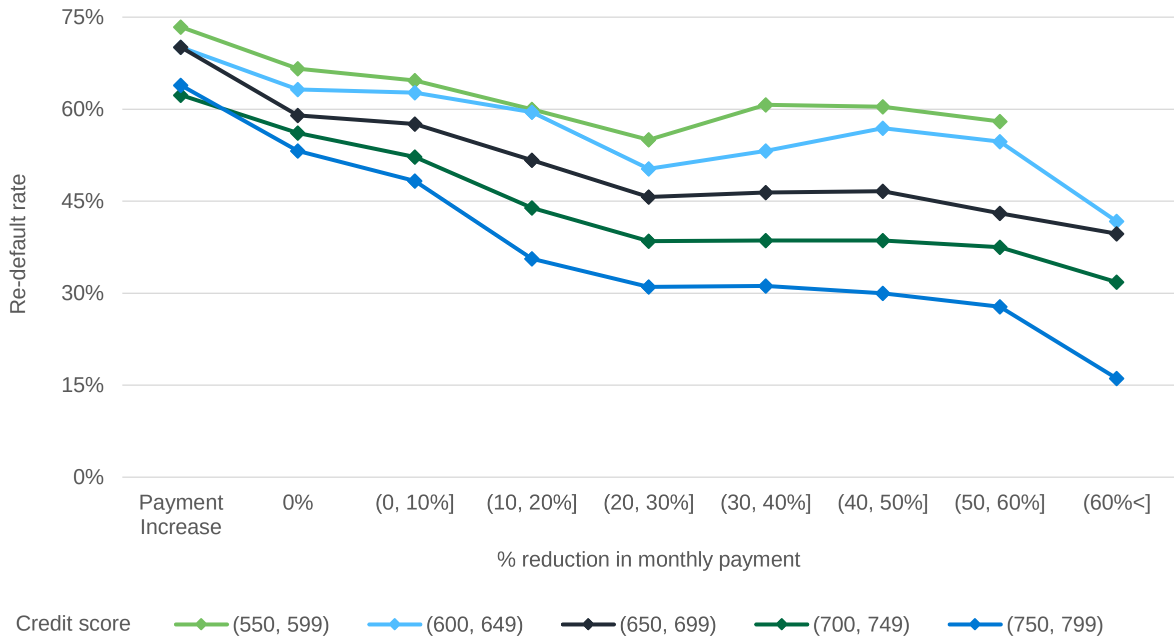
FIGURE 4: RE-DEFAULT RATE BY PAYMENT REDUCTION AMOUNT (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY)



Borrower default rates generally decrease as the payment reduction amount increases, up to around a 20% to 30% reduction, where there appears to be a diminishing return. Borrowers who receive no payment reduction or an increase have the highest default rates, at approximately 68%. In all cases, re-default rates are significantly greater than default rates on performing loans. The default rate on new originations varies between 1% and 14% over the life of the mortgages and is heavily dependent upon economic conditions.

Recall that credit score and amount of payment reduction are positively associated. Borrowers with higher credit scores also tend to default at lower rates relative to those with lower credit scores. To qualify whether the decreased default rates at higher payment amounts are a function of higher credit borrowers, default rates by payment reduction amount and credit score are broken out in Figure 5. Note that cross-sections containing less than 30 borrowers were omitted. A table of results is also available in the appendix.

FIGURE 5: RE-DEFAULT RATE BY PAYMENT REDUCTION AND CREDIT SCORE COHORT (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY, LOW COUNTS EXCLUDED)



The traditional relationship between credit score and re-default rate does hold, where borrowers with higher credit scores default less compared to borrowers with lower scores. The gap between the default rates and credit scores appears to widen as the payment reduction amount increases, suggesting that higher credit score borrowers do benefit more as the payment reduction increases, though it does appear that re-default decreases do begin to slow after a 30% payment reduction. Cumulative default rates are presented in Figure 6 to tease out timing as a component of the diminishing return to higher payment reduction amounts:

FIGURE 6: PERFORMANCE FOR LOANS MODIFIED BETWEEN 2008 AND 2012

CUMULATIVE RE-DEFAULT RATE					QUARTERS FROM MODIFICATION					
Payment reduction	**N**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8+**
Payment increase	1384	8.1%	16.3%	31.9%	40.1%	46.0%	49.0%	52.2%	55.6%	68.5%
0%	16995	4.0%	6.9%	18.0%	26.8%	33.3%	38.6%	42.5%	45.5%	60.0%
(0, 10%]	6556	10.6%	15.8%	24.0%	29.8%	34.4%	38.5%	41.7%	44.3%	57.0%
(10, 20%]	18309	5.2%	9.3%	15.9%	21.7%	26.4%	30.2%	33.5%	36.0%	50.3%
(20, 30%]	17768	2.4%	4.6%	9.0%	13.8%	18.3%	22.2%	25.5%	28.1%	43.2%
(30, 40%]	16137	2.4%	3.8%	7.9%	12.1%	16.2%	19.5%	22.7%	25.3%	43.5%
(40, 50%]	12096	2.6%	3.8%	6.7%	10.3%	14.0%	17.3%	20.3%	22.9%	43.7%
(50, 60%]	6264	3.5%	4.5%	6.8%	9.7%	12.9%	16.4%	18.8%	20.8%	41.4%
(60%<]	554	2.9%	4.0%	5.1%	7.6%	9.7%	13.5%	15.3%	17.3%	34.7%
TOTAL	96063	4.0%	6.6%	12.6%	18.0%	22.7%	26.6%	29.9%	32.5%	48.8%

While there is less differentiation in ultimate default rates up to 2012 after the payment reduction reaches 30%, it does appear that from three to seven quarters following modification there is some observed benefit of higher payment reduction amounts. The chart does not extend beyond eight quarters as default rates tend to stabilize further out from the immediate point of receiving loss mitigation. Roughly 12% of re-defaults for loans without a payment reduction or an increase occur within the first two quarters following modification, suggesting these borrowers re-default especially quickly compared to borrowers who received a higher payment reduction. Whether or not there is a substantial long run benefit to payment reductions beyond 30% is questionable, however it is evident that some level of payment reduction does provide immediate financial aid.

To evaluate other influences on re-default rates, a linear regression analysis was performed on the data controlling for various effects that are known to influence mortgage default rates. The analysis was performed iteratively by adding variables across five models to evaluate the impact each set of variables has on the payment reduction coefficient. Coefficient estimates from the linear probability models are provided in Figure 7. The full set of model variables and coefficients can be found in the appendix.

FIGURE 7: MODELED EFFECT OF PAYMENT REDUCTION ON RE-DEFAULT PROBABILITY

	(1)	(2)	(3)	(4)	(5)
P(Default = 1) =	**BIVARIATE**	**ADD BORROWER CHARACTERISTICS**	**ADD LOAN CHARACTERISTICS**	**ADD ECONOMICS**	**ADD RANDOM LOAN EFFECTS**
Payment reduction %	-0.00016**	-0.00013**	-0.00013**	-0.00014**	-0.00051**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)

Heteroskedastic consistent standard error rounded to 5 decimals given in parentheses, *p < .05, **p < .01

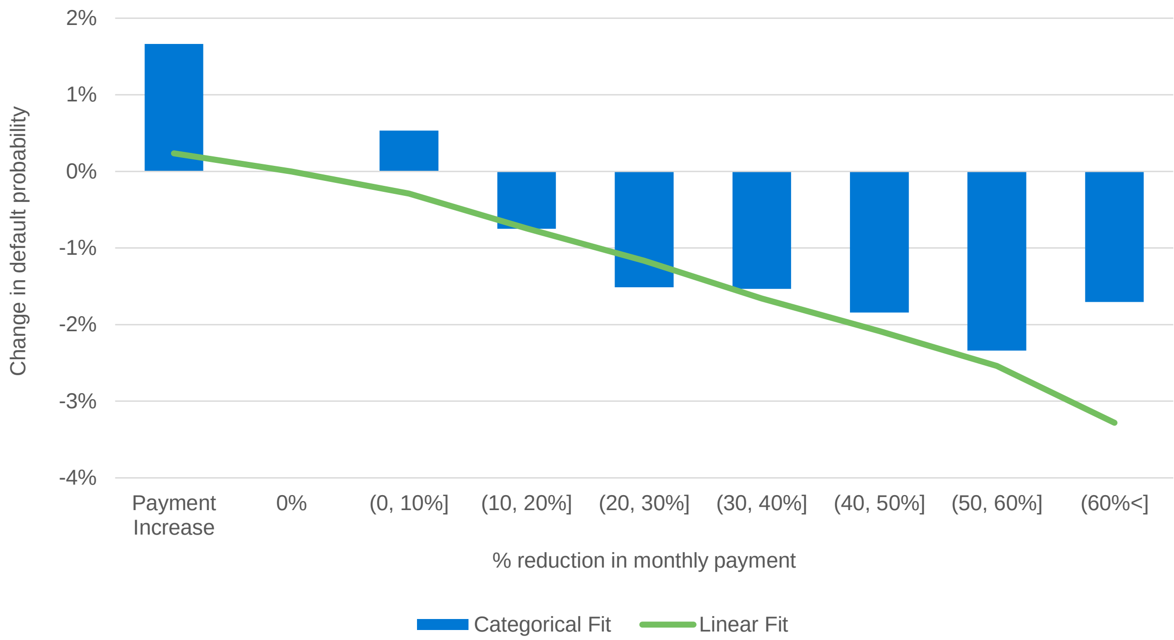
Consider that the period-to-period default rate in the sample is approximately 1.1%. The initial regression including only the payment reduction would suggest that on average, a 1% decrease in the monthly payment results in a 0.02 percentage point reduction in the period default rate. For example, if the average re-default rate is 50%, a 1% decrease in the monthly payment would result in a re-default rate of 49.98%. Given that the average payment reduction amount for borrowers who *receive a payment reduction* is roughly 30%, the average borrower with a payment reduction is 0.5 percentage points less likely to default in any given period relative to borrowers with a 0% payment reduction.

After borrower characteristics, which traditionally explain default risk, enter the model, the estimated magnitude of payment reduction decreases by about 16%. From here, the coefficient becomes relatively stable while also being statistically significant across models as loan characteristics and economics are included. After controlling for loan-specific random effects, the estimate on payment reduction changes substantially, to be about twice as large as in the original bivariate specification. This coefficient indicates that a 1% decrease in the monthly payment results in a 0.05 percentage point reduction in the period default rate, all else constant. For example, if the average re-default rate is 50%, a 1% decrease in the monthly payment would result in a re-default rate of 49.95%. At the average payment reduction, borrowers are 1.5 percentage points less likely to re-default in any given period compared to borrowers who received a 0% reduction in their payment following modification. While monthly effects appear small, the cumulative impact is large enough where lenders and borrowers should be interested. The finding is suggestive that, conditioned on risk characteristics, higher amounts of payment reduction does lead to lower risk of re-default.

To understand this change, consider that a random effects model helps capture variation between groups that is generally uncorrelated with the predictor variable of interest. In this instance, we assume that an unobservable loan-specific effect is randomly drawn from a population of potential effects, but that this effect does not determine the distribution of payment reduction within. There may be some covariance between the payment reduction and loan-specific effects, and after adjusting for the non-independence of observations within each loan (i.e., different time periods of the same loan are inherently tied closer together than different time periods across different loans), the coefficient changes accordingly. For example, we may have accounted for differences in loan servicer practices as they pertain to default and payment reduction, or local housing market conditions not captured by the present economics. Demographics may also be captured by these effects, though it becomes difficult to quantify any association between demographic characteristics and payment reduction received given that the literature is nonexistent, and the data is not available.

To qualify the linear fit chosen in the model as opposed to a different transformation, an alternative version of model 5 is run using discretized versions of payment reduction. Coefficient estimates are compared to the estimated marginal percentage point change in period default probability from the linear fit using the average within each bucket as the reference. Given that the bucket specification is arbitrary, this analysis is mostly illustrative. The marginal effect is displayed in Figure 8.

FIGURE 8: MARGINAL CHANGE IN DEFAULT RATE FROM PAYMENT REDUCTION (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012 MODEL ESTIMATES: CATEGORICAL VERSUS LINEAR FIT)



Estimates from the categorical model generally line up with those from the linear estimate though there are a few notable deviations. The default probability is estimated to increase compared to no payment reduction within the (0, 10%] bucket, though the intuition is that loans within this bucket receiving a reduction closer to 0 are probably similar to borrowers who received no payment reduction. Within bucket distributions of payment, reduction will have a significant impact on the coefficient estimate from this model. The categorical model does pick up on some level of diminishing return around a payment reduction of 20% but estimates of the marginal effect over this horizon appear to closely match those from the linear model. Those receiving a greater than 60% payment reduction appear to behave rather anomalously, though this group is by far the smallest cohort with only 554 loans represented and is therefore more likely to produce volatility. The linear estimate is sufficient for establishing a general idea of how payment reduction affects default probability. The conclusion here is that to a certain degree, servicers should try to achieve as high of a payment reduction as they can if they want to optimize borrower performance following modification. This conclusion, however, does not consider the cost of loss mitigation to either the servicer or investor in the mortgage.

The homogeneity of the effect of payment reduction on default probability is measured across cohorts of borrower characteristics. This provides insight into whether certain groups are impacted identically or if there is some variation on where payment reduction may be effective. Model 5 is estimated within quartiles of the following variables: FICO, age at the time of modification, and estimated income at origination and shown in figure 9. We derive income by taking the borrower's debt to income ratio and divide it by the original balance of the loan. This variable was excluded from the regression due to the likelihood of measurement error.

FIGURE 9: ANALYSIS OF HETEROGENEITY: PAYMENT REDUCTION ON DEFAULT

COHORT	COEFFICIENT	ST. ERR.	SIG.
Credit score			
Quartile 1	-0.00034	0.00002	**
Quartile 2	-0.00040	0.00002	**
Quartile 3	-0.00055	0.00002	**
Quartile 4	-0.00072	0.00002	**
Implied income			
Quartile 1	-0.00035	0.00002	**
Quartile 2	-0.00061	0.00003	**
Quartile 3	-0.00056	0.00003	**
Quartile 4	-0.00053	0.00002	**
Loan age when modified			
Quartile 1	-0.00074	0.00002	**
Quartile 2	-0.00043	0.00002	**
Quartile 3	-0.00045	0.00002	**
Quartile 4	-0.00028	0.00002	**

Heteroskedastic consistent standard error given in parentheses, *p < .05, **p < .01

In relative terms, there are some differences in the effect of payment reduction for different groups of borrowers. Specifically, borrowers of the lowest income and credit score quartiles see lower return to each incremental payment reduction amount. This would suggest that these borrowers need a greater amount of assistance to reduce their default probability at the same rate as a higher income or higher credit score individuals. Conversely, the highest credit score borrowers appear to have the highest marginal benefit from each additional percent of payment reduction. If the goal from a policy standpoint is to keep borrowers in their homes, it may be helpful for greater amounts of payment reduction to be given to low-income and low credit score homeowners if there is a limited budget built in for modification costs.

Loans that receive a modification early in their life appear to receive a much greater benefit from payment reduction than older loans. If the goal is to keep borrowers in their homes for as long as possible, it may be beneficial to allocate more attention to those who default early given that the reduction in default probability is greater. Loans that are older will likely have more balance paid off and may be eligible for alternative resolutions that don't result in foreclosure, or at the very least a policy that wouldn't be as costly.

Given these differences, all the estimated coefficients are negative in direction, statistically significant, and relatively close to the estimate from the full sample regression. There may exist other cohorts on which differences are greater not available in the data.

IV: Conclusion

The amount of payment reduction provided to borrowers in loss mitigation appears to be a predictive variable in determining subsequent borrower performance, even independent of available risk characteristics. Generally, higher amounts of payment reduction result in lower re-default rates, though there may be some level of diminishing returns after a borrower's payment is reduced beyond 30%. Special attention may also need to be given to groups that traditionally struggle to pay their mortgages, given that they may need a greater payment reduction to achieve the same re-default target compared to an average borrower.

Additional attention has been given as of recently to loss mitigation efforts, both in private and public sectors. Modifications post-pandemic are subject to unique conditions given the high levels of home price appreciation experienced between 2020 and 2022 coupled with high interest rates following Federal Reserve efforts to curb inflation. Given that terms are usually dictated by the going market rate, many borrowers would see a potential payment increase under traditional loss mitigation. This is problematic given that we've observed the payment increase can lead to higher rates of default, almost 70% in this sample. A more aggressive deferral strategy may need to be coupled with payment reduction until rates are cut.

This paper has established that payment reduction and default probability are negatively correlated in a controlled setting, however it has not been determined that this is the most effective method to prevent borrower default. Additional research may look at a broader pool of borrowers to measure the effectiveness of different default alternatives if the goal is to determine prescriptive policy. It is important to consider the human element, that the goal should be to design programs that help keep borrowers in their homes. In addition, this paper does not consider the costs of loss mitigation. We focus attention on the efficacy of loss mitigation as measured by the change in borrower payment.

CONTACT

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V: Appendix

FIGURE 10: MARGINAL RE-DEFAULT RATE BY QUARTER AND PAYMENT REDUCTION (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY)

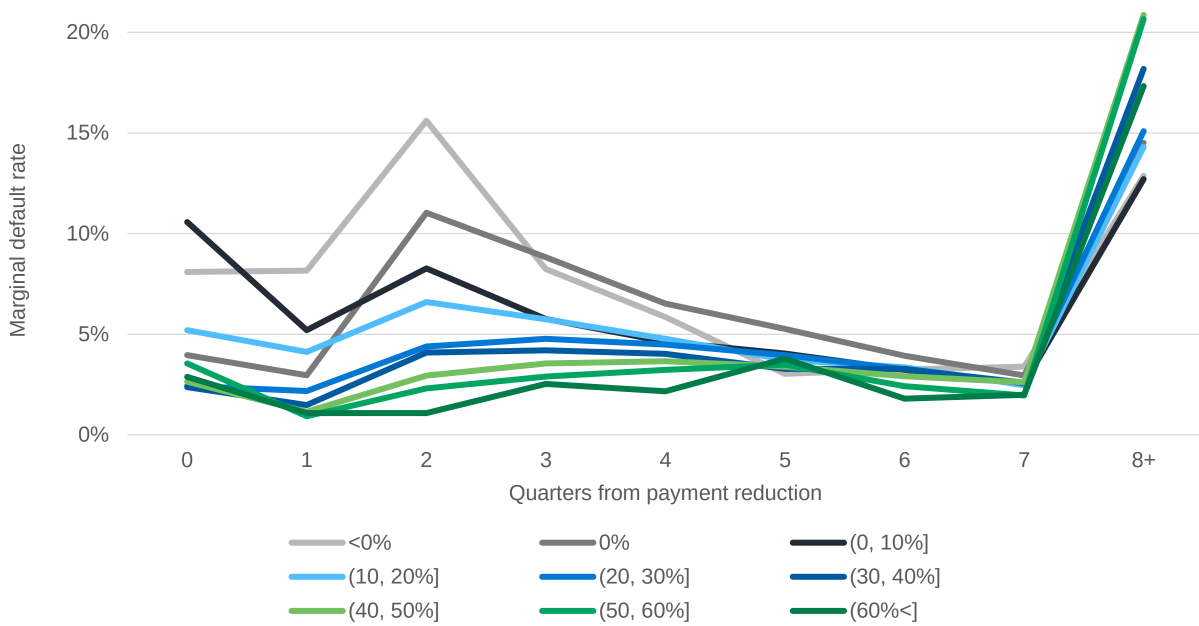

FIGURE 11: CUMULATIVE RE-DEFAULT RATE BY QUARTER AND PAYMENT REDUCTION (STANDARD FIXED RATE MORTGAGES MODIFIED BETWEEN 2008 AND 2012, PURCHASE ONLY)

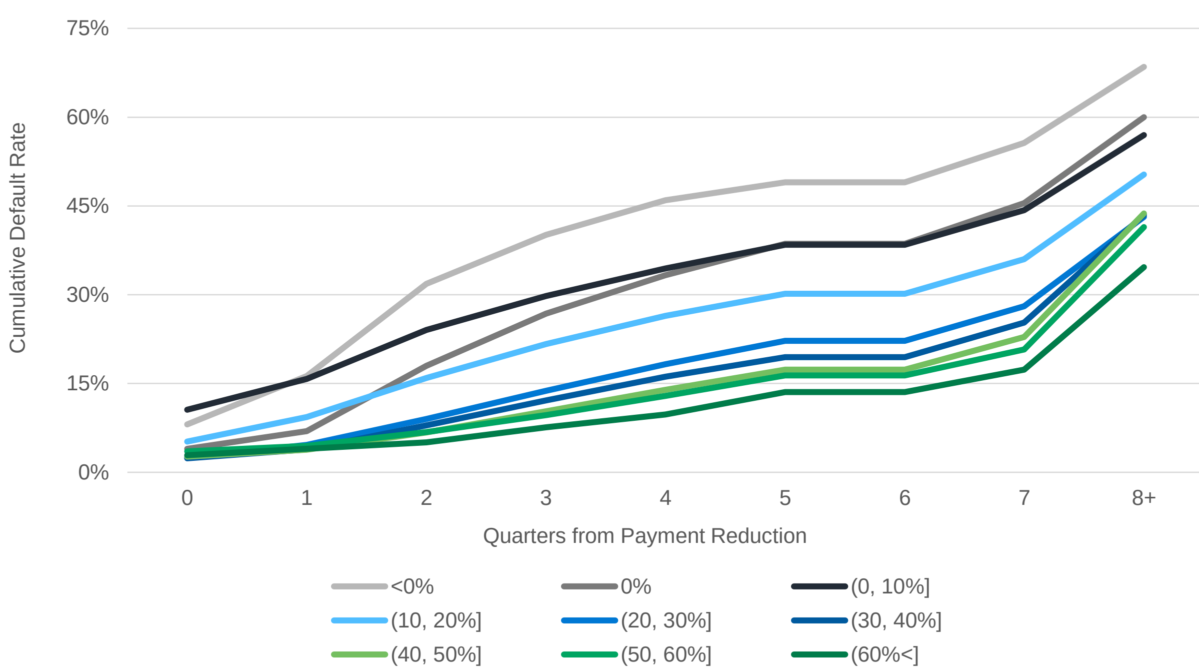

FIGURE 12: RE-DEFAULT RATE BY PAYMENT REDUCTION AND CREDIT SCORE FOR LOANS MODIFIED BETWEEN 2008 AND 2012

	CREDIT SCORE						
PAYMENT REDUCTION	**(300, 549)**	**(550, 599)**	**(600, 649)**	**(650, 699)**	**(700, 749)**	**(750, 799)**	**(800, 850)**
Payment increase		65%	61%	61%	58%	65%	
0%	56%	57%	60%	59%	62%	63%	74%
(0, 10%]	46.9%	51.5%	57.5%	54.1%	54.6%	52.9%	
(10, 20%]	46.0%	46.8%	44.5%	38.9%	37.3%	34.0%	35.8%
(20, 30%]	44.4%	40.4%	35.4%	32.8%	28.0%	24.4%	22.9%
(30, 40%]	36.0%	40.3%	36.4%	32.3%	28.6%	24.1%	17.8%
(40, 50%]	40.5%	38.7%	36.3%	31.3%	27.0%	22.3%	15.7%
(50, 60%]	42.4%	33.8%	31.9%	26.6%	24.2%	19.6%	21.0%
(60%<]			35.5%	29.5%	18.0%	15.5%	

*Cross sections with n < 30 were excluded.

FIGURE 13: MODELED EFFECT OF PAYMENT REDUCTION ON RE-DEFAULT PROBABILITY

P(DEFAULT = 1) =	(1) BIVARIATE	(2) ADD BORROWER CHARACTERISTICS	(3) ADD LOAN CHARACTERISTICS	(4) ADD ECONOMICS	(5) ADD RANDOM LOAN EFFECTS
Payment reduction %	-0.00016**	-0.00013**	-0.00013**	-0.00014**	-0.00051**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Log (new monthly payment)		0.00062	-0.00033*	-0.00026	-0.00250**
		(0.00011)	(0.00013)	(0.00014)	(0.00029)
Credit score		-0.00004**	-0.00003**	-0.00003**	-0.00007**
		(0.00000)	(0.00000)	(0.00000)	(0.00000)
Debt to income		0.00004**	0.00001**	0.00002**	0.00001
		(0.00000)	(0.00000)	(0.00001)	(0.00001)
Loan to value		0.00008**	0.00009**	0.00009**	0.00025**
		(0.00000)	(0.00000)	(0.00001)	(0.00001)
First time home buyer			0.00044**	0.00050**	0.00082**
			(0.00011)	(0.00012)	(0.00028)
UPB remaining (%)			0.01139**	0.01168**	0.00635**
			(0.00056)	(0.00062)	(0.00075)
Age at modification			-0.00023**	-0.00020**	0.0000**
			(0.00000)	(0.00000)	(0.00001)
Age since modification			-0.00016**	-0.00012**	0.00023**
			(0.00000)	(0.00000)	(0.00000)
Unemployment rate (%)				0.00058**	0.00123**
				(0.00004)	(0.00005)
Home price appreciation				-0.00021	-0.02021**
				(0.00040)	(0.00057)
Primary spread (30Yr - 10Yr)				-0.00367**	-0.00573
				(0.00038)	(0.00032)
Fixed effects					
Loan guarantor			X	X	X
State			X	X	X
Vintage			X	X	X

Heteroskedastic consistent standard error rounded to 5 decimals given in parentheses, *p < .05, **p < .01