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Analyzing the Relationship Between Mortgage Interest Rates and Delinquency Probability: A Causal Investigation

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Abstract: This study examines how interest rates affect the chance of delinquency in the mortgage market in the United States. Although it has been demonstrated that a number of the borrowers and loan-related factors influence the likelihood of delinquent, it is difficult to pinpoint how interest rates affect delinquency because lenders tend to charge higher interest rates for borrowers who pose a greater risk to them. To disentangle the causal effect of interest rates from the "price of risk" effect, we exploit a discontinuity in the U.S. mortgage market using a proprietary dataset of 222,087 mortgages. Borrowers whose FICO credit score is immediately above 620 enjoy lower financing costs than borrowers immediately below. Borrowers on either side of the cutoff are not homogeneous, however; to deal with this, we employ a partially linear regression model. Results of the study revealed that the impact of interest rates is quite favorable on the likelihood of misbehavior. According to one estimate, ceteris paribus, a 1% rise in the introductory interest rate causes a 2.66 % increase in the likelihood that the same borrower will default. Therefore, it is recommended that agency issues, particularly the lack of motivation to screen borrowers brought on by widespread securitization, partially disguise the impact of interest rates on delinquency.

Keywords Credit Score, Delinquency Probability, Interest Rates, Mortgage Market, Regression Discontinuity

1. Introduction

The risk of delinquency and default is the major driver of financing cost for homeowners. Several characteristics of the borrower and the loan are known to influence the probability of delinquency. These characteristics include, among others, loan-to-value ratio, credit score, income of the borrower, and interest rate. While for most characteristics the relationship is straightforward, finding the causal effect of interest rate on delinquency probability is hard. To assess the magnitude of this effect, a simple regression coefficient is not enough: lenders charge a higher interest rate for higher-risk borrowers, so a good estimate must separate this "price of risk" effect from the pure "increase in payment" effect.

In this paper, we aim to address the endogeneity problem and provide an unbiased estimation of the magnitude of a 1-unit change in the interest rate on the delinquency rate. By sidestepping this endogeneity problem, our study contributes to a more accurate understanding of the relationship between interest rates and delinquency rates, which has important implications for policymakers, particularly in the context of managing monetary policy to control inflation.

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Our study identifies the impact of home mortgage interest rates on delinquency probability using a proprietary dataset. The dataset includes loan and borrower characteristics of 222,087 mortgages originated mostly from 2004 to 2007. We run an unconditional regression of delinquency on initial interest rate and other relevant characteristics including credit score (FICO), income, and loan-to-value ratio. As anticipated, we find that interest rate is positively correlated with delinquency probability. To disentangle the causal effect of interest rate from other factors, we identify a discontinuity in the average interest rate and apply the Regression Discontinuity (RD) method.

Specifically, borrowers with a credit score below 620 are automatically considered subprime; because of a long-standing convention in the U.S. mortgage market, their loans are much less likely to be securitized or sold. Therefore, when a borrower's credit score is at or above this cutoff point, he or she is offered a more favorable interest rate. Borrowers to the immediate left of this cutoff point would have similar creditworthiness as those to the immediate right side. Without the exogenous cutoff point, borrowers on both sides would be offered similar terms for the loan. Therefore, focusing on this neighborhood around the cutoff point enables us to identify how the probability of delinquency responds to an interest rate change, other things being equal.

The RD method is valid under the additional assumptions that borrowers cannot manipulate their credit score and that other characteristic variables do not jump at the same cutoff point (see Lee et al. [1] for further discussion). If borrowers can manipulate their score, the jump in interest rate is not exogenous. If other variables jump at the same cutoff point, it is unclear what causes a jump in delinquencies (if any). With these issues properly addressed, the result from RD method suggests that the interest rate has a strong, positive effect on the delinquency probability; in fact, addressing these issues if anything strengthens the conclusion. We confirm that the direction of the effect is same as the result from unconditional analysis, but the magnitude is higher.

Our paper is related to the literature on mortgage delinquency. Jiang et al.[2] (2014) document the “liar’s loans” problem, where poorly-documented loans have significantly higher delinquency rates. Several papers document that delinquency rates are heterogenous across borrower groups by employment situations or personal characteristics. For example, Mocetti and Viviano[3] (2017) find that, after the financial crisis, job losses of borrowers almost double the delinquency probability. Agarwal et al.[4] (2017) show that financial professionals are less likely to become delinquent. Kim et al.[5] (2020) demonstrate that financial literacy overconfidence has a positive effect on mortgage delinquency. In their study, individuals who demonstrated appropriate confidence levels exhibited a lower likelihood of engaging in delinquent behavior than those who displayed overconfidence. Relatedly, Chhatwani[6] (2022) argues that personal characteristics matter to mortgage delinquency during COVID-19: financially literate borrowers are less likely to delay their mortgage repayment during the COVID-19 pandemic, and personality traits such as neuroticism, extroversion, and conscientiousness serve as moderating variables in the relationship between financial literacy and mortgage delinquency. Finally, Hansen and Ellie Donne[7] (2022) examine how financial literacy, financial education, personal and other factors, and socio-economic characteristics affect the delinquency of mortgage payments among homeowners and find that financial literacy plays a crucial role in mortgage payment behavior.

The rest of the paper is structured as follows. Section 2 presents results from an unconditional analysis and discusses its limit. Section 3 provides empirical design and results from the RD method while checking its validity. Section 4 concludes.

2. Unconditional Analysis

We perform an unconditional regression of delinquency on loan and borrower characteristics including the initial interest rate. We choose initial interest rate above current interest rate for two

reasons. First, our delinquency rates are at most five years into the mortgage. Most adjustable-rate mortgages have a fixed rate for the first 3 or 5 years, thus making the initial rate more representative of the financing cost sustained by the borrower so far. Second, we do not know what "current rate" means for delinquent mortgages. The rate could be the rate as of a default event, as of the last payment, or as of today; or it could be a penalty default rate. In any case, the large majority of mortgages in the dataset have current rate equal to initial rate.

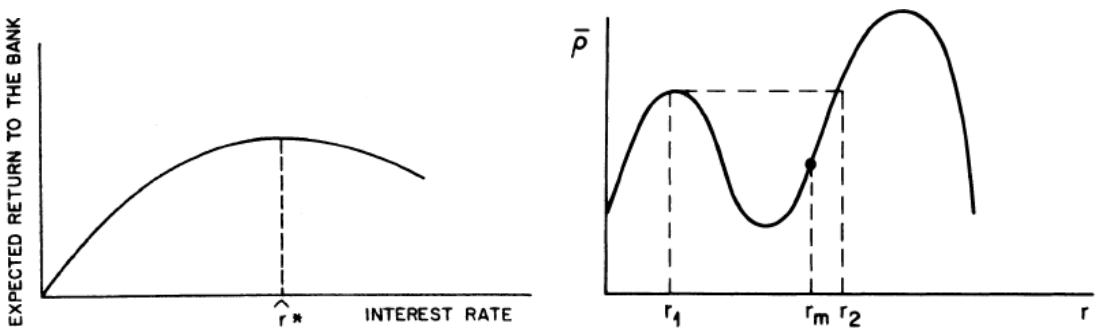
Other loan characteristics we consider are loan-to-value ratio, original balance, whether it is through broker, and whether full documentation was required. For borrower characteristics, we include credit score, monthly income, age, gender, ethnicity/race and whether they are self-employed.

In order to eliminate outliers, we winsorize initial interest rate and monthly income at 1 percent size (results are not qualitatively different than with the raw variables). We estimate the following specification:

$$Deliq_i = \beta \cdot int_i + \gamma \cdot X_i + \epsilon_i \tag{1}$$

where, $Deliq_i$ is 1 if there is a default event or 0 otherwise, and X_i is a vector of characteristic variables except for interest rate. The column Unconditional in Table 2 shows the coefficient estimates. The results suggest that a 1 percent rise in interest rate is associated with a 1.7 percent increase delinquency probability. However, interest rate is likely correlated with the residual of equation (1). In other words, the lender will require a higher interest rate if the borrower is perceived to have higher ex-ante probability of default. In fact, the lender will simultaneously choose a level of collateralization, a maturity, and an interest rate for a given borrower such as to maximize its expected return; this expected return is not a linear function of the interest rate, and the optimum need not be unique under mild assumptions (see [Fig. 1] from Stiglitz and Weiss[8] , 1981). In [Fig. 1], the lender chooses the interest rate factoring in the effect it will have on the default probability of the borrower. This is not only an academic point, as we will see below.

Ideally, we would want to assign different interest rates to pairs of otherwise identical borrowers and see the outcome. In practice, one could find a variable which correlates with interest rate but not correlated with delinquency probability and use it as an instrument to address this endogeneity. Unfortunately, considering interest rate is essentially the compensation of counterparty risk that the lender bears, anything that would affect interest rate should be correlated with delinquency probability. A third approach, closely related to instrumental variables, is the Regression Discontinuity method.



[Fig. 1] Interest Rate and the Expected Return to the Bank (Stiglitz and Weiss[8], 1981)

3. Regression Discontinuity: Research Methodology, Results, and Discussion

3.1 Identification of the Discontinuity

The FICO credit score is a measure of the overall credit quality of the borrower and it is one of the most influential factors in the determination of mortgage interest rate. Borrowers with a higher credit score get more favorable interest rates. When the FICO score reaches 620, the funding cost of the lender is suddenly reduced because the loan is much more likely to be sold or securitized, due to a long-standing convention of the US mortgage market.

To the extent that some of this saving is passed on to the borrower, we have identified a "jump" in interest rate that has little to do with borrower characteristics since the credit risk of a borrower with a FICO score of 619 should not be very different from that of a borrower with 620. [Fig. 2] clearly verifies this discontinuity. Note that, in [Fig. 2], the distribution of interest rates becomes bimodal as FICO score exceeds 620 due to the addition of "teaser" mortgages with a low introductory rate. On the left side of the cutoff point, 620, average interest rate decreases by 70 basis points per 100 FICO score while the slope of decrement is 1.7 percent to the right of 620. At the cutoff point, the average interest rate level jumps down by 1.5 percent. The statistical significance of the jump can be also verified from the following regression:

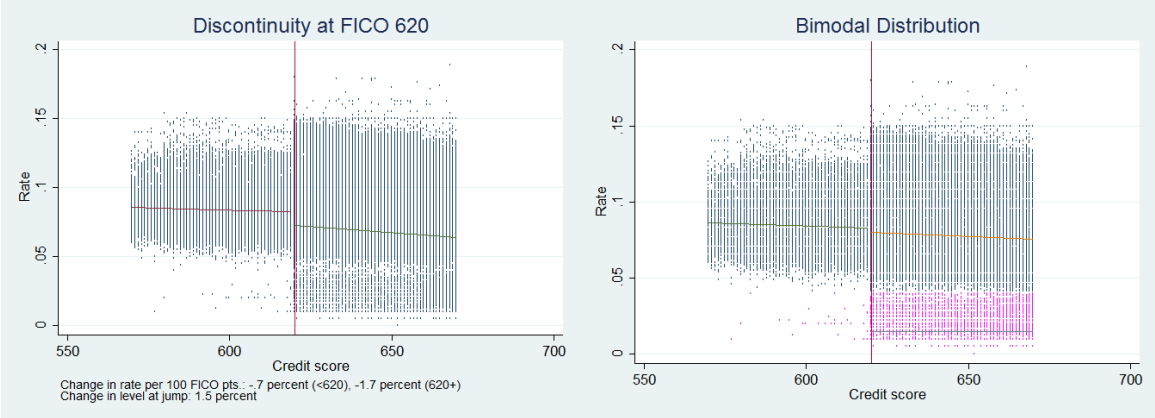
$$Rate_i = \beta_0 + \beta_1 \cdot High_i + (\beta_2 + \beta_3 \cdot High_i) \cdot FICO_i + \epsilon_i \quad (2)$$

where $High_i$ is 1 if $FICO_i \geq 620$, otherwise 0. Considering the high homogeneity of variables in a given geographic location, all regressions use standard error clustered by Metropolitan Statistical Area (MSA). Also, to have readable coefficients, we rescale some variables: we divide FICO and *Monthly Income* by 1,000 and *Original Balance* by 1,000,000. The left panel of [Table 1] reports the result of this regression and it shows that the coefficients on the "high" and the interaction variable are strongly significant. A two-sample t-test shows that the difference in mean interest rate between loans above and below the cutoff is 1.61 percent with strong significance.

[Table 1] Identification of a Jump in Interest Rate

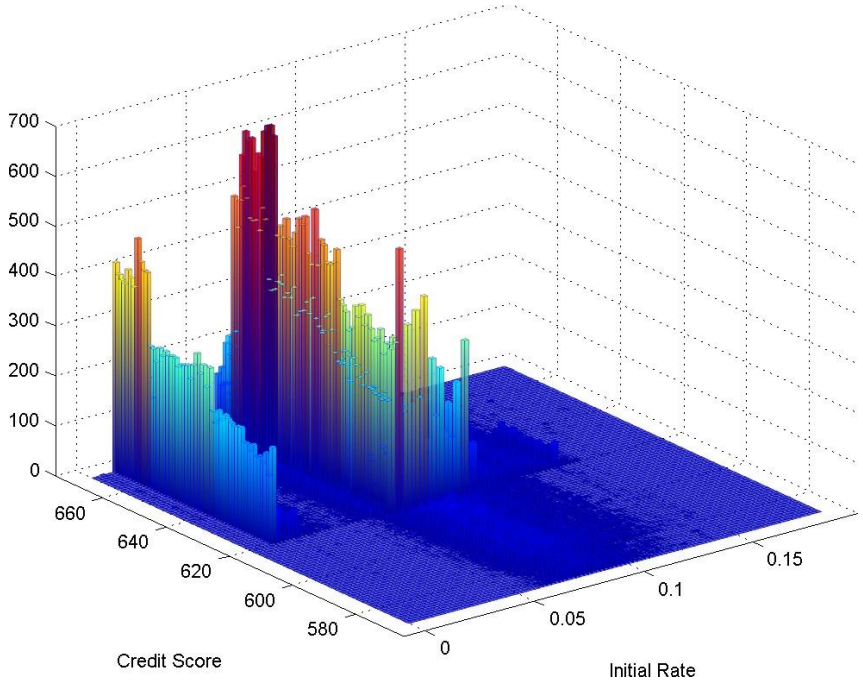
	With All Observations		Without Lower Group	
	Coefficient	t-stat	Coefficient	t-stat
FICO	-0.074433	-6.98***	-0.069973	-6.72***
High	0.047346	4.39***	0.005518	0.59
FICO·High	-0.092093	-5.50***	-0.013141	-0.88
Constant	0.128468	20.45***	0.125897	20.45***
Adj. R2	0.038699		0.01721	
Chow p-value	0.000		0.000	
N	222078		191644	

The nature of the discontinuity is sharp at 620 as shown in left panel of [Fig. 2]. A set of observations with noticeably lower interest rate suddenly appears starting at FICO 620 and above. If there were a probabilistic function for the assignment of a rate and if the probability of being assigned lower rates increased as FICO rises higher than 620, we would see the gradual appearance of this new set of observations. In other words, the discontinuity is not fuzzy. Moreover, we discover the distribution of initial rate becomes bimodal immediately at the cutoff point.



[Fig. 2] Regression Discontinuity of Interest Rates as a Function of Credit Scores

[Fig. 3] represents the joint distribution of FICO score and interest rate. The distribution is strong evidence of the sharp appearance of the set of borrowers with significantly lower rate. The division is sharp enough to allow us to visually separate borrowers at or above 620 into two groups - one with higher interest rate (Upper Group) and the other with lower interest rate (Lower Group). The average rate of the Lower Group is as low as 1.5 percent and this implausibly low rate is due to a particular variety of mortgage loan contracts. Such loans offer low interest rates at the beginning, but the rate steps up at a predetermined time depending on the specific contract. In practice, these are called "introductory mortgages" or "teaser mortgages". These types of mortgages are offered only to borrowers with at least 620 FICO score. The "treatment" therefore consists of offering this and other options, in addition to the more traditional ones, only if the FICO score is greater or equal to 620. In fact, we have anecdotal evidence that this type of mortgages was offered on purpose to reduce the borrower's probability of default; sometimes with the hope, or the calculation, that the borrower would indeed refinance out before things went south.



[Fig. 3] Joint Distribution of Credit Score and Initial Rate

Without the appearance of the Lower Group, the discontinuity is less significant. The right panel of [Fig. 2] shows the regression line once we exclude the Lower Group and the jump is not as distinct as in the left panel. Once we estimated regression (2) using only observations in the Upper Group, the right panel of [Table 1] shows that the coefficients β_2 and β_3 become individually insignificant, even though they are still jointly significant, while β_1 (the slope) is essentially unvaried. In untabulated results, the p-value of a joint F-test on the two "high" coefficients (a Chow test for structural breaks) is still very close to zero. Indeed, excluding the Lower Group, one can still find a significant jump in interest rates at 620, but the magnitude is second-order; the same can be said for the corresponding jump in delinquency rates. If we include the Lower Group, initial interest rate decreases by about 0.86% (versus 0.22% without) and delinquencies decrease by 0.81% (versus 0.34%). This in spite that most "teaser" mortgages have already reset to a higher rate by the time the sample was taken.

This reinforces our claim that the jump is caused by the Lower Group. Considering that appearance of Lower Group is triggered when the score is at least 620 or higher, we confirm that the discontinuity is sharp.

The basic assumption that makes RD possible is that borrowers in the narrow neighborhood centered at the cutoff point have essentially the same creditworthiness. Without the exogenous cutoff, borrowers in this neighborhood would have a similar delinquency probability. Since the interest rate jumps at the cutoff, however, there will be a difference in delinquency rate between the two sides. Thus, the discontinuity lets us identify the pure effect of rate change on delinquency probability, holding other factors equal.

3.2 Basic Design

We focus therefore on the borrowers in the interval [619, 620]. The specification is the same as equation (1), but using only observations in this interval. The column RD (619 vs. 620) in [Table 2] reports the coefficient estimates. The coefficient of initial rate is now higher: 1 percent increase in the initial rate is now associated with an increase in delinquency probability of 3.52 percent. This number is significantly higher than the unconditional regression estimate.

[Table 2] Effect of Interest Rate on Delinquency Rate

	Unconditional		RD (619 vs. 620)		RD (619 vs. 621)	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Initial Rate	0.01707	14.99***	0.03518	11.13***	0.02661	4.67***
FICO	-0.00291	-30.11***	0.01523	0.69	-0.00818	-0.88
Loan-to-Value	0.00116	7.35***	0.00253	6.88***	0.00059	1.45
Original Balance	-0.07392	-2.20*	0.09922	1.24	-0.07727	-0.76
Monthly Income	0.00394	10.51***	0.00103	0.67	0.00199	0.96
Age	-0.00316	-23.14***	-0.00443	-8.38***	-0.00478	-6.96***
Gender	-0.00015	-0.06	0.01515	1.04	0.00863	0.48
Black	0.05673	5.16***	0.14369	4.37***	0.02675	1.09
Hispanic	0.01819	2.00*	0.00632	0.24	0.04696	2.44*
Asian	-0.01959	-2.33*	-0.11487	-3.07**	-0.09603	-1.63
Full Documentation	-0.08438	-14.47***	-0.04725	-2.40*	-0.06437	-2.34*
Broker	0.04605	7.94***	0.04953	1.72	0.06704	2.06*
Self-Employed	-0.01974	-4.33***	-0.01352	-0.87	-0.00263	-0.10
Adj. R2	0.05241		0.06762		0.04950	
N	197,253		6,202		3,088	

3.3 Manipulation of Credit Score and Data Selection

One of the challenges for the identification through discontinuity is the possibility of manipulation of FICO score and hence the possibility that (i) the distribution of FICO score in the population is not smooth around 620, and (ii) the credit quality of borrowers in the neighborhood of the cutoff point is not the same. If "bad" borrowers could manipulate the credit score to just above 620, borrowers with FICO 620 would be less creditworthy than those with FICO 619. Jiang et al. [9] (2014) and Keys et al. [10] (2010), while admitting the possibility of manipulation or credit management, provide justification from a different angle that this issue does not impair validity of findings from RD analysis. However, we want to provide a numerical estimate of the magnitude of an effect which we know to be positive, so we need to worry about both positive and negative bias. We notice that the distribution of FICO is not smooth, jumping down from 6,213 loans at FICO 620 to little more than 2,910 loans at 621. This indicates a clustering of people on the specific number 620. This phenomenon could be due to the borrowers' aggressive attempts to achieve a lower rate, so that they continuously shop for a mortgage while they "manage" the credit score and accept a loan offer as soon as they hit 620. As an alternative explanation, given that it is difficult to manipulate one's credit score with such surgical precision, this could be evidence of false reporting. To buttress this hypothesis, we provide some otherwise implausible facts.

First, we find that Full Documentation loans have lower delinquency rates than non-Full Documentation loan for every single FICO score above 600, except for 620. For scores below 600, full-documentation loans still have lower delinquency rates in about 80 percent of cases. This could be due to structural differences in the two pools of people, or simply to the fact that there are fewer datapoints and estimates are more volatile. That is, borrowers who went through more strict screening at 620 show worse ex-post credit quality. This is consistent with the hypothesis that there are many borrowers at 620 who aggressively attempted to lower the rate. This group of borrowers might have worse credit quality than borrowers left to 620.

Second, the percentage of brokered loans is highest at 620 out of all FICO scores. We conjecture those brokers, who have a strong incentive to sell more loans, may have falsified FICO scores, typically entering "620" in place of a lower score. Therefore, we decide to exclude the FICO 620 group from further analysis. Dropping this sample should not negatively affect the validity of the RD analysis because we still have enough observations at FICO 621, and the probability of being treated at 621 is not any different than at 620. The distance is still only two points and from 621 onwards the distribution of FICO is, indeed, smooth.

The column RD (619 vs. 621) in [Table 2] also reports the coefficient estimates using FICO scores of 619 and 621 only. After we exclude the observations at 620, the causal effect of a 1 percent rise in interest rate is estimated to be a 2.66 percent increase in delinquency probability, showing still significantly higher sensitivity than the result from the unconditional analysis. Comparing the results of this regression with the previous one, we see that using the FICO 620 sample (particularly rich of "bad" borrowers) overestimates the effect of a change in interest rates.

3.4 Controlling for Jumps in Covariates

To ensure the validity of the result from RD analysis, one must check if other covariates jump at the same cutoff. If there are discontinuities in other variables at 620, it is unclear which "jumping variable" contributes how much to the change in delinquency probability. To identify this, we run two-sample t-tests for all covariates of interest except for the interest rate. [Table 3] indicates many covariates jump even within the window we consider, but in a direction that is likely to strengthen the results. Borrowers at FICO 621 show several signs of lower reliability (less full documentation loans, more brokered loans,

and more self-employed borrowers). In spite of this, they default less. This suggests that the actual effect of a lower interest rate is even greater than the measured jump; if the borrowers at 621 were as carefully selected as the borrowers at 619, they would default even less.

[Table 3] Jumps in Selected Variables

	Whole Sample			FICO $\in\{619, 621\}$		
Name	Low - High	t-stat	P-value	Low - High	t-stat	P-value
Initial Rate	0.0161	85.0643	0.0000	0.0086	6.9172	0.0000
Delinquency Rate	0.1645	53.6759	0.0000	0.0081	0.3665	0.7140
Loan-to-Value	5.6506	35.7056***	0.0000	3.6289	3.3156***	0.0009
Monthly Income	-1354	-30.6951***	0.0000	-411	-1.4581	0.1449
Full Documentation	0.4471	144.6536***	0.0000	0.3792	16.9103***	0.0000
Broker	-0.0423	-23.7966***	0.0000	-0.0483	-3.9959***	0.0001
Self-Employed	-0.0912	-33.8434***	0.0000	-0.0558	-3.1719**	0.0015

In order to neutralize the jump of covariates, we apply the partially linear regression model proposed by Jiang et al. [10] (2014). The specification we want to estimate is:

$$Deliq_i^j = f(FICO_i^j) + \gamma \cdot X_i^j + \epsilon_i^j \tag{3}$$

where, the superscript *j* indicates all the observations are from samples with FICO score *j*. That is, we group all the observation into j baskets, one for each FICO score. We subtract the mean of each basket from (3), yielding:

$$Deliq_i^j - \overline{Deliq}^j = f(FICO_i^j) - f(\overline{FICO}^j) + \gamma \cdot (X_i^j - \overline{X}^j) + (\epsilon_i^j - \overline{\epsilon}^j) \tag{4}$$

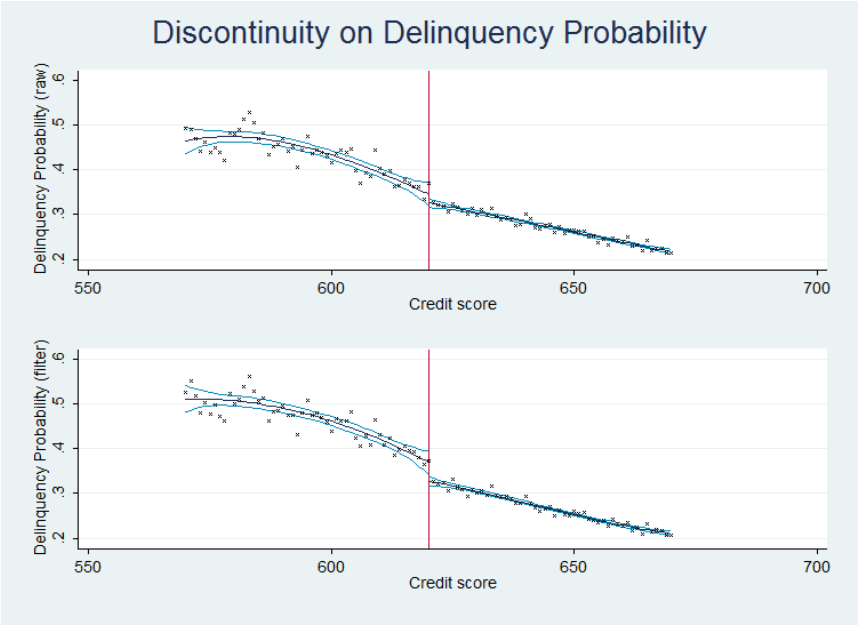
where, $\overline{V}^j$ is the average of variable V_i^j within the *j* basket. Since $FICO_i^j = \overline{FICO}^j$, the first term on right hand side of the equation is cancelled out. We obtain:

$$Deliq_i^j - \overline{Deliq}^j = \gamma \cdot (X_i^j - \overline{X}^j) + (\epsilon_i^j - \overline{\epsilon}^j) \tag{5}$$

and γ can be estimated by regressing $Deliq_i^j - \overline{Deliq}^j$ onto $(X_i^j - \overline{X}^j)$. This is equivalent to a simple regression with FICO fixed effects. By plugging the estimated coefficients $\hat{\gamma}$ into (3), we can obtain the filtered delinquency probability:

$$FilteredDeliq_i^j = Deliq_i^j - \hat{\gamma} \cdot X_i^j \tag{6}$$

Therefore, *FilteredDeliq* is the change in delinquency probability after controlling for jumps in all covariates except interest rate. Figure 4 displays the result graphically. The upper panel is the raw delinquency rate per FICO score with 95 percent confidence bands. The lower panel shows the *filtered* delinquency rate. Delinquency probability at 620+ is outside of the 95 percent confidence bands of delinquency probability at 620-, and vice versa. These results indicate that the discontinuity gap is widened after controlling other covariates jump. The source of discontinuity in delinquency rate is therefore due to the jump in initial interest rate.



[Fig. 4] Discontinuity on Delinquency Probability

[Table 4] reports the raw delinquency probabilities, the filtered one and also the average interest rates at the two FICO points we focus. As seen in the [Fig. 4], the negative jump becomes larger in delinquency probability after we control jump of covariates. That is, the jump in delinquency probability is indeed due to the interest rate discontinuity. This result reinforces the validity of result from RD analysis. Our results are consistent with Jiang et al. [9] (2014) and Keys et al. [10] (2010), who documented the interest rate discontinuity.

[Table 4] Delinquency Probability after Controlling and Interest Rate at Cutoff Points

FICO	Raw Delinquency	Filtered Delinquency	Interest Rate
619	33.4594%	36.4080%	8.1139%
621	32.6461%	32.7518%	7.2526%

4. Conclusion

This study examines how interest rates affect the chance of delinquency in the mortgage market in the United States. The U.S. mortgage market displays a marked structural break between borrowers whose credit score is below 620 and those at or above 620. At least until 2007, loans to borrowers who made the cut could be easily securitized and sold. Perhaps as a result, these borrowers were offered lower rates and were able to further reduce their financing cost by optimizing over a much wider menu of mortgages, including adjustable-rate mortgages with a low introductory rate. Such mortgages effectively allowed borrowers to make low payments for a given amount of time while further building their credit and hence their ability to refinance into less expensive mortgages.

We exploit this discontinuity to show that interest rate has a large influence on delinquency rates. The effect is partially masked by the fact that borrowers just above the cutoff, conditional on being approved for a mortgage, are riskier than borrowers just below. This could be a direct result of agency problems, and specifically the lack of incentive to screen borrowers caused by widespread securitization. To deal

with this problem, we employ a partially linear regression model as in Jiang et al.[9](2014). Our best estimate is that, ceteris paribus, the same borrower would have a 2.66 percent higher probability of delinquency for a 1 percent increase in the initial interest rate.

This figure should be taken with two caveats with respect to external validity. First, given the discontinuity used, this figure is best interpreted as the effect of a change in interest rates on a subprime borrower. Prime borrowers, who are the majority, are likely to have a higher resilience to shocks to the cost of financing, due to more stable jobs and in general lower loan-to-income ratios. Second, this sample contains 2008 data on mortgages originated mostly in the 2004-2007 period. It is possible that the true cost of "teaser" mortgages would not have shown yet and that some of these borrowers, unable to refinance, defaulted later. In any case, our lower bound estimate for the effect of interest rate is 1.71 percent, still an economically significant number.

Our paper provides important policy implications by quantitatively measuring how the risk in the economic system would rise in response to changes in interest rates. This understanding is particularly relevant in the current period of tightened monetary policy aimed at managing inflation rates. By shedding light on this mechanism, our findings can inform policymakers and help them make more informed decisions when setting interest rates.

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