A Farewell to Equality: Monetary Policy Implications of Heterogeneous Mortgage Refinancing*

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Abstract

We show that credit score heterogeneity dampens monetary policy transmission through fixed-rate mortgages. Using Fannie Mae Single-Family data, we show that a one-percentage-point reduction in the mortgage rate increases the refinancing probability for borrowers with excellent credit scores twice as much as for good credit score borrowers. Our refinancing model implies that credit score heterogeneity dampens consumption response to monetary policy through the refinancing channel by one-third and results in a 50% higher wealth increase for excellent borrowers compared to good ones in the long run. Lower credit score borrowers have higher marginal propensities to consume but refinance less often.

JEL Codes: E32, E43, E52, E58, G21, G51

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Fixed-rate mortgages (FRMs) are a significant component of household debt in the United States and a key channel of monetary policy transmission.[1] Monetary policy can stimulate household consumption and wealth by lowering mortgage costs through refinancing. However, refinancing is subject to rigorous underwriting criteria,[2] preventing some households from taking advantage of lower rates. This heterogeneity creates lasting imbalances in consumption and wealth between households with different refinancing opportunities, dampening the efficacy of monetary policy.

Using U.S. monthly loan-level data and a heterogeneous agent model, this paper shows that borrowers' credit score heterogeneity limits monetary transmission through the FRM channel and increases wealth and consumption inequality between credit score groups. Our main empirical finding is that borrowers with lower credit scores are less likely or able to refinance their mortgages even if their coupon rates are much higher than market mortgage rates. Our model suggests that their consumption and wealth responses are weaker than those of their higher credit score counterparts. Allowing all groups to refinance at the same rate, regardless of their credit scores, smooths these imbalances without affecting debt delinquency rates.

To document credit score heterogeneity of refinancing response to monetary policy and motivate a heterogeneous agent model of refinancing, we analyze Fannie Mae Single-Family Loan-Level historical data. We estimate that a one-percentage-point reduction in the mortgage rate increases the refinancing probability for borrowers with a FICO credit score of 800 twice as much as that for borrowers with a score of 700. Our refinancing model implies that this heterogeneity dampens consumption response to monetary policy through the FRM channel by one-third and results in a 50% higher wealth increase for excellent borrowers compared to good ones in the long run.

In the empirical part of the paper, we establish the credit score heterogeneity

[1] Goodman, McCargo, Golding, Parrott, Pardo, Hill, Kaul, Bai, Strochak, Reyes and Walsh (2019) document that in the U.S., 30-year FRMs add up to 40% of all household liabilities.

[2] The fraction of denied refinance applications has been historically higher than that of denied purchase applications. According to HMDA data, in 2007, banks declined 30% of refinancing and 20% of purchase loan applications; in 2017, those numbers were 19% and 12%, respectively.

of the refinancing response to changes in mortgage rates in three steps. First, we show that, for each rate gap, there are significant differences in the refinancing hazards of borrowers in lower and upper quartile credit score distribution, even after controlling for observable loan characteristics and fine geographic-by-time fixed effects. Second, we argue that credit score heterogeneity is more important than heterogeneity across other loan characteristics, such as debt-to-income (DTI) and loan-to-value (LTV) ratios. Finally, we exploit exogenous changes in monetary policy to measure the marginal effect of credit score heterogeneity on refinancing. By instrumenting mortgage rate changes with monetary shocks, we avoid bias caused by omitted variables that affect both mortgage rates and refinancing through channels distinct from monetary policy.

We start by constructing a measure of potential savings that a household would realize by refinancing its mortgage at the current mortgage rate. Our measure at the household level is the rate gap, which is the difference between the current loan rate and the predicted refinance rate for that household.

In the first step of the analysis, we estimate the refinancing hazard as a non-parametric function of the rate gap, credit score quartile, and other loan characteristics. Pooling observations across time, we sort borrowers into rate gap bins and credit score quartiles and calculate the fraction of refinanced loans in each rate gap bin and credit score quartile. We then show that refinancing hazards for each credit score quartile exhibit a step-like shape: refinancing rates are low and constant among loans with negative rate gaps and are high and constant among loans with positive rate gaps. However, among mortgages with positive rate gaps, loans with credit scores in the upper quartile have a much higher probability of refinancing than loans in the lower credit score quartile.

We then show that the credit score heterogeneity in refinancing is significant and more extensive than that in other borrower characteristics – DTI, LTV, and remaining balance. It is robust to (i) using an alternative definition of rate gap aiming to remove borrower fixed effects, (ii) controlling for payment history rather than the remaining balance, and (iii) aggregating to quarterly frequency and a 3-digit ZIP code level. The episodes of mortgage rate decrease drive this result, which is much smaller during cycles of tight monetary policy.

We instrument rate gaps with high-frequency monetary shocks to avoid endogeneity issues arising from confounding factors. Those include household liquidity constraints during recessions, such as the inability to pay the fee for premature mortgage payout. High-frequency identification yields the unexpected part of the monetary policy shock because it controls the market expectations by considering rate changes only within a small window. A one-percentage-point increase in the rate gap leads to a 1.25 percentage-point increase in the likelihood of refinancing for borrowers with a credit score of 800. However, this likelihood rises by only 0.54 percentage points for borrowers with a credit score of 700. The marginal impact of a 50-point increase in FICO credit score amounts to 27% of the average monthly refinancing rate.

Refinancing heterogeneity in any characteristic affects aggregate spending only if that characteristic correlates with the marginal propensity to consume (MPC). While vast refinancing literature has identified a number of demographic borrower characteristics that affect refinancing, estimating the correlation between these characteristics and spending is difficult because of the limited data. However, borrowers' credit scores, unlike other demographic characteristics, directly relate to their borrowing constraints and, thus, MPCs. To show that the credit score is a crucial and prohibitive criterion for mortgage refinance approval, we merge refinancing loan rejection rates from the HMDA data with credit scores from the Fannie Mae data. By narrowing down the analysis to attentive borrowers, i.e., ones who applied for a refinance loan, we show that credit scores in an MSA negatively correlate with loan rejection rates. This finding implies that even if the borrower has access to liquid assets but does not have a sufficiently high credit score, the lender will not originate a loan.

In the theoretical part of the paper, we develop a heterogeneous agent model with FRMs to infer MPCs of different credit score groups and quantify the importance of this heterogeneity for aggregate consumption and wealth inequality. First, we show that the heterogeneity that we document dampens aggregate monetary transmission and negatively affects the well-being of lower credit score groups in the long run. Second, we demonstrate that easing refinancing frictions allows high MPC borrowers to benefit from monetary expansions and smooths out long-run wealth disparities between credit score groups.

To show that heterogeneity dampens aggregate consumption response, we compare aggregate response to rate cuts in the homogeneous economy and the heterogeneous economy. The homogeneous economy is based on the refinancing environment in Berger, Milbradt, Tourre and Vavra (2021), where agents have the same access to credit markets. In the heterogeneous economy, agents differ in their credit scores, which evolve over time. This novel feature of the model endogenously generates differential MPCs across credit score groups.

The model features a consumption-savings decision in an incomplete market setting, labor income risk, refinancing of the FRMs, and the evolution of credit scores. We employ a standard consumption-savings framework with a borrowing constraint. Households face individual labor income risk and aggregate interest rate risk, which plays a role of monetary policy. Each household owns a house financed by a FRM with a refinancing option. Refinancing enters via a Calvo-style exogenous shock – agents refinance at Poisson arrival times only if their rate gap is positive. The Calvo model for refinancing is consistent with the step-like hazard function we observe from the data.

The novel feature of our model is credit score heterogeneity. The credit score affects the household's ability to refinance its FRM and the interest rate it pays for liquid debt borrowing. Each household decides whether to make the mortgage payment, affecting its credit score. Missing a mortgage payment causes a decrease in credit score. If a household keeps up with its payments, its credit score changes according to an exogenous mean-reverting random process.

The way we model credit scores is in line with the evolution of credit scores documented in the literature. First, credit score predicts the probability of a borrower repaying a loan. If this probability is low, a borrower can neither refinance the mortgage nor borrow unsecured debt at a low rate. Second, credit score predicts past debt delinquency, which implies a higher likelihood of future delinquency since an already-low credit score suggests lower losses from missing additional payments. Borrowers with low credit scores in our model will thus be more likely to be financially constrained and exhibit high MPCs.

Our analysis implies that the aggregate consumption response through the

FRM channel to a one-percentage-point cut in the aggregate interest rate is lower by one-third in the economy with credit score heterogeneity than in the economy without credit score heterogeneity. Monetary policy affects household consumption through two channels. The first of these is the wealth effect: a cut in interest rate decreases the return on wealth for all agents and makes short-term borrowing cheaper for higher credit score borrowers. Second is the refinancing effect: an interest rate cut provides higher credit score households with a refinancing option, allowing them to reset their mortgage rate to a lower one and free up disposable income for additional consumption. Since higher credit score borrowers have lower MPCs than borrowers in the homogeneous economy, a rate cut results in a dampened consumption response.

Furthermore, we show that heterogeneity causes long-lasting wealth and consumption differences between credit score groups. At its peak, which occurs 14 years after the shock, the increase in the wealth of the low credit score group is 50% lower than that of the high credit score group. Heterogeneity in refinancing contributes to consumption inequality as well: the peak response of the low credit score group's consumption, occurring 4.5 years after the shock, is 40% lower than for the high credit score group. The reason behind these disparities is that borrowers with lower credit scores cannot refinance their mortgages and end up paying higher coupons every month.

Finally, we demonstrate that a policy that addresses heterogeneity in refinancing smooths out these disparities in wealth and consumption while keeping delinquency rates low. To do that, we consider monetary transmission a counterfactual economy that preserves credit score heterogeneity but allows the low credit score group to refinance at the average refinancing rate in data.

Our paper extends the existing literature on the mortgage market in monetary policy implementation[3] on both empirical and theoretical fronts. On the

[3]The first papers in this strand of literature focused on adjustable-rate mortgages that are exposed to interest rate changes directly – see Bhutta and Keys (2016), and DiMaggio, Kermani, Keys, Piskorski, Ramcharan, Seru and Yao (2017). The most recent research studies the FRM market because 30-year FRMs are the dominant type of mortgage contract in U.S. housing – see Berger et al. (2021), DiMaggio, Kermani and Palmer (2020), Beraja, Fuster, Hurst and Vavra (2018), and Eichenbaum, Rebelo and Wong (2022).

empirical front, our main contribution is to show that credit score heterogeneity is significant and more critical for aggregate refinancing in the U.S. than other loan characteristics, such as DTI and LTV ratios, that matter in the refinancing literature. Since credit score, unlike demographic characteristics, directly relates to credit constraints and thus MPCs, our theoretical model endogenously generates differential MPCs, thus contributing to the literature on redistribution effects of monetary policy and heterogeneous agent models.[4]

Two papers that are closely related to ours are Berger et al. (2021) and Eichenbaum et al. (2022). They show that refinancing rate incentives vary over time because FRMs allow borrowers to *choose* whether they want to be exposed to a particular rate. Berger et al. (2021) argue that future expansionary policy will have weaker effects on refinancing since many FRM holders managed to refinance during the years of low rates that followed the Great Recession. We show that even though some borrowers could benefit from refinancing, they remain locked in the previous rates because of difficulties in getting new loans. These borrowers are the ones who are most likely to boost spending. Our heterogeneous agent model allows us to estimate how costly it is for policymakers to ignore this heterogeneity, in addition to the consequences of holding rates low for a long time.

The rest of the paper is organized as follows. Section 1 describes the data we use in our empirical analysis. Section 2 documents empirical results on credit score heterogeneity. Section 3 outlines a refinancing model showing that credit score heterogeneity dampens housing wealth response to monetary policy. Section 4 concludes.

1 Data

To show that borrowers with lower credit scores are less likely to refinance in response to expansionary monetary policy, we use Fannie Mae Single-Family

[4]Theoretical work in this strand includes Hedlund, Karahan, Mitman and Ozkan (2017), Kaplan, Moll and Violante (2018), Auclert (2019), Kaplan, Mitman and Violante (2020), Guren, Krishnamurthy and Mcquade (2021).

Loan-Level historical dataset.[5] Mortgages owned by Fannie Mae make up 26% of the total mortgage market, which, combined with other agency mortgage-backed securities, adds up to 61.3% of the mortgage market as of the first quarter of 2019. In May 2018, securities outstanding in the agency market totaled $6.7 trillion, 42.8% of which was Fannie Mae.[6] This mortgage-level panel data contains information about loan-specific characteristics at the time of origination for fully amortizing, full documentation, single-family, conventional FRMs purchased by Fannie Mae. The panel data tracks each loan monthly from origination until the borrower voluntarily pays it off or it is involuntarily foreclosed. Since each loan in the dataset has a unique identification number, implying that we cannot track the same borrowers over time, we treat each loan as belonging to a new borrower.

Our analysis includes loans originated from January 2000 to March 2019. The data on loan performance extends through December 2021. We limit the sample to FRMs with a maturity of 30 years. 30-year FRMs make up over 60% of all mortgage contracts for our sample period.

Since we conduct our analysis on the monthly frequency where the unit of observation is a loan-month, we work with a 10 percent random sample of the Fannie Mae Single-Family data set to ease the computational burden. We build our sample by selecting a 10 percent random sample of loans originated in each quarter during our sample period.[7] The total number of FRMs is 3,580,928, resulting in 149,070,748 loan-month observations.

In our analysis, we employ the information on the remaining loan balance in each month from origination to prepayment, outstanding (fixed) interest rate, FICO credit score, DTI, LTV, loan purpose (cash-out refinance, rate refinance, purchase of a new house), and a 3-digit ZIP code recorded at the mortgage origination.[8,9] We additionally construct three time-varying variables: the refinancing indicator, current LTV ratio, and rate gap.

[5] Retrieved from http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html.

[6] See Goodman et al. (2019)

[7] We experimented with selecting a 10 percent random sample of all loans from the dataset, and all the results were statistically indistinguishable across these methodologies.

[8] In what follows, we use the terms "FICO credit score" and "credit score" interchangeably.

[9] Debt in DTI refers to the flow debt payment rather than a stock of debt.

To construct the refinancing indicator, we treat mortgages prepaid voluntarily before maturity (as opposed to the foreclosure) as refinanced and focus on total refinancing regardless of prepayment reason, rate decrease, or equity extraction.

To control for refinancing incentives arising from variation in home equity alone, we construct the current LTV ratio for each loan in our sample using ZIP-level house prices from the Zillow database.

We construct rate gap, $gap_{it} = m_i^* - \hat{m}_{it}$, by calculating the difference between the current fixed interest rate on the outstanding loan, m_i^*, and the predicted rate, $\hat{m}_{it}$, for a new FRM originated in period t given borrower/loan characteristics for FICO, LTV, and DTI at the time of origination from the following regression:

$$m_{it} = \alpha_0 + \alpha_1 CS_{it} + \alpha_2 CS_{it}^2 + \alpha_3 LTV_{it} + \alpha_4 LTV_{it}^2 + \alpha_5 DTI_{it} + \alpha_6 DTI_{it}^2 + \alpha_7 r_t^m + \varepsilon_{it} \quad (1)$$

where for each borrower i with a loan originated in t, CS denotes a FICO credit score, LTV denotes the loan-to-value ratio, DTI denotes the debt-to-income ratio, and r_t^m denotes the 30-year FRM average in the U.S. from Primary Mortgage Market Survey (PMMS) by Freddie Mac.[10] This specification explains about 90 percent of the variation in outstanding mortgage rates.[11]

Online Appendix A2 displays summary statistics for key observable variables in our sample. Although Fannie Mae has a minimum qualifying credit score of 620 and we focus only on conventional loans, we treat our sample as representative of the population of 30-year FRMs. In Online Appendix A3, we show that the mean mortgage rate time series for contracts in our sample heels the market 30-year FRM average.

We use three additional datasets in our analysis. First, we use the Recursion's Cohort Analyzer to show that credit score heterogeneity results from Section 2.2 hold for 30-year FRMs purchased by Freddie Mac. Second, we use daily futures data downloaded from the Bloomberg terminal to construct monetary policy shocks for Section 2.3. Third, we use the Recursion's HMDA analyzer to access refinancing loan rejection rates and show that they negatively correlate with credit scores in Section 2.4.

[10] Retrieved from the FRED at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

[11] See Online Appendix A1 for regression (1) estimation results.

2 Empirical Results

This section shows that the refinancing response to monetary policy depends on borrowers' credit score distribution. Our analysis comprises three steps. First, we provide visual evidence suggesting that credit score distribution affects refinancing and is a potential source of heterogeneity. Second, motivated by this observation, we find significant differences in refinancing across borrowers in different credit score quartiles. We first plot a prepayment hazard as a function of the interest rate gap for credit score quartiles. We then provide evidence that credit score heterogeneity is more important than that across DTI and LTV ratios, even after controlling for fine geographic-by-time fixed effects. Third, we exploit exogenous changes in monetary policy to estimate the marginal effect of credit score heterogeneity on refinancing while avoiding bias caused by omitted variables that affect both mortgage rate and refinancing through channels distinct from monetary policy. Finally, we provide evidence consistent with the hypothesis that credit constraints are the reason behind lower refinancing among lower credit score borrowers.

2.1 Credit Score Distribution as a Source of Heterogeneity

We motivate the exploration of credit score as a source of refinancing heterogeneity by providing two aggregate time-series relationships. The first shows that the unconditional refinancing rate is higher for borrowers with higher credit scores. The second illustrates rate and credit score dynamics for the borrowers in the same cohort, who virtually had the same mortgage rates. Even among borrowers with the same mortgage rates, we observe that borrowers with higher credit scores refinance most actively.

Figure 1 shows monthly refinancing rates for borrowers in the lower and upper quartiles of the credit score distribution. The figure suggests that during several episodes of loose monetary policy – quantitative easing QE1 and quantitative easing QE2, the refinancing rate is higher for borrowers with higher credit scores.

Second, borrowers with higher credit scores are the ones who refinance most actively, even among borrowers with similar rate incentives to refinance. The top row of Figure 2 shows mortgage rate and credit score dynamics for the borrowers in the same cohort. In the left panel, we plot the average mortgage rate of outstanding contracts that originated in May 2000 (blue line) and the current market mortgage rate (orange line). In the right panel, we plot the average credit score of outstanding contracts that originated in May 2000. The market mortgage rate declined from 8.5% in 2000 to 3.8% in 2019. If the interest rate is the only determinant of refinancing, we would see the average cohort rate falling over time because borrowers with the highest incentives to refinance would have prepaid their mortgages and left the sample. However, the average rate of outstanding loans in this cohort does not vary, while their holders' average credit score is dropping, suggesting that borrowers with a higher credit score were more likely to refinance. In Online Appendix A4, we show that this result holds for other cohorts.

This evidence suggests that the power of the FRM channel for monetary policy transmission depends both on mortgage interest rates and the credit scores of borrowers. Suppose holders of high-rate mortgages have low credit scores, preventing them from refinancing. In that case, the effects of monetary policy are smaller than suggested by the distribution of the outstanding rates alone.

2.2 Heterogeneous Response of Refinance to Mortgage Rates

In this subsection, we document a substantial positive correlation between refinancing and credit score after controlling for rate gaps and other borrower characteristics. To do so, we construct refinancing hazards by rate gaps for borrowers in each credit score quartile.

We start by looking at refinancing, pooling all monthly observations for contracts originated in 2000–2019. We then sort loan-months to 20 basis point (bp) wide gap bins and four credit score groups corresponding to quartiles of credit score distribution and estimate a non-parametric relationship between refinancing and rate gaps, credit score, and their interaction using the following regression:

$$\mathbb{1}\{\text{Refi}_{it}\} = \alpha + \beta_b \mathbb{1}\{gap_{it}^{bin}\} + \gamma_b \mathbb{1}\{CS_i^{bin}\} + \delta_b \mathbb{1}\{gap_{it}^{bin}\} \times \mathbb{1}\{CS_i^{bin}\} + X_{it}\Gamma + \eta_{ZIP} + \varepsilon_{it} \quad (2)$$

where $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced;

$\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy for the gap bin of loan i in month t; $\mathbb{1}\{CS_i^{bin}\}$ is a dummy for the quartile bin of loan i in month t; X_{it} is a vector of loan characteristics which includes a quadratic in LTV, a quadratic in DTI, a quadratic in loan age, and dummy for whether the current loan was itself a new purchase, a cash-out refinance or a rate refinance, lagged ZIP-level house price; η_{ZIP} is a 3-digit ZIP-code fixed effects. Standard errors are two-way clustered by a 3-digit ZIP code and month.

Figure 3 shows the resulting monthly refinancing hazard given by the point estimates for coefficients $\beta + \delta$ for borrowers with credit scores in lower (blue line) and upper (orange line) quartiles with their 95% confidence bands.[12] Two observations stand out. First, in line with Berger et al. (2021), there is a positive relationship between rate gaps and probability to refinance: loans with positive rate gaps are more likely to refinance than loans with negative rate gaps. Second, positive-gap loans with FICO credit scores in the upper quartile have a one percentage point higher probability of refinancing for the same interest rate gap than loans with FICO scores in the lower quartile.

While higher credit score borrowers seem to have higher sensitivity of refinancing to rate gaps, it could be the case that other factors that affect refinancing also vary with rate gaps, similar to credit scores. For example, borrowers with lower credit scores, higher LTV ratios, higher DTI ratios, or smaller mortgage balances might be more likely to have larger rate gaps and lower refinance probabilities simultaneously.

To argue that the credit score heterogeneity in refinancing is significant and more extensive than in other borrower characteristics – LTV, DTI, and remaining balance, we employ linear probability models and estimate them at a monthly frequency. Our regressions take the following form: for the loan i at month t, we estimate

$$\mathbb{1}\{\text{Refi}_{it}\} = \alpha + \beta gap_{it} + Char_{it}\gamma + gap_{it} \times Char_{it}\delta + X_{it}\Gamma + \varepsilon_{it} \tag{3}$$

where $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; gap_{it}

[12] For the linear probability model estimates of regression (2), see Online Appendix A5.

is a rate gap of household i in month t; $Char_{it}$ is a vector of household i's borrower characteristics including credit score, LTV ratio, DTI ratio, and the remaining balance; $gap_{it} \times Char_{it}$ is the interaction between rate gap and borrower characteristics of household i in month t; X_{it} denotes a vector of controls.[13] We also include geographic fixed effects and origination year-month fixed effects. The standard errors are double-clustered on a 3-digit ZIP code and a monthly level. We normalize all variables, except the interest rate gap, around the corresponding sample means.

Our specification controls for many observable variables affecting refinancing and rate incentives. Including year-month fixed effects means that identification occurs entirely from ZIP-code variation rather than aggregate time-series variation within a month. For example, controls for the year 2003 will take care of a large spike in refinancing in 2003, documented by Justiniano, Primiceri and Tambalotti (2022). Moreover, the year-month-by-ZIP-code fixed effects guarantee that identification comes from ZIP-code-specific monthly variation within a month, not from time-invariant regional differences. That eliminates concerns that differences in demographics, lender concentration, or other slower-moving local characteristics might drive results.

Table 1 provides the estimation results. Column (1) provides estimates from a specification that includes all controls, origination year-month, a complete set of year-month-by-ZIP fixed effects, and only one interaction term: that of rate gap with credit score. Higher credit score borrowers are significantly more likely to refinance in response to the rate gap increase. A one-percentage-point increase in the rate gap is associated, on average, with a 0.74 percentage-point higher probability of refinancing for borrowers with a credit score of 750 (mean credit score). For borrowers with a credit score of 800 (one standard deviation above the mean credit score), this probability increases by 0.98 percentage points.

In column (2) of Table 1, we add the interaction of the rate gap with the LTV ratio. The addition of this interaction does not materially change our estimate

[13] Controls include the number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing, or a rate refinancing, indicators for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown).

for the rate gap sensitivity between different credit score borrowers. Its sign is positive but small in magnitude. One reason for the non-intuitive sign is that borrowers with higher LTV ratios and large rate gaps also have higher remaining balances. This specification omits the interaction of the gap with the remaining balance and leads to an upward bias of the coefficient.

In column (3) of Table 1, we add the interaction of the rate gap with the DTI ratio. Its sign is negative but small in magnitude, suggesting that borrowers with a DTI ratio of 45% (one standard deviation above mean DTI) are 0.04 percentage points less likely to refinance than borrowers with a DTI ratio of 35% (one standard deviation below mean DTI).

In column (4) of Table 1, we add the interaction of the rate gap with the remaining balance. Interestingly, the interaction of the gap with LTV becomes insignificant (and negative). Loans with higher remaining balances are more likely to refinance and more responsive to interest rates – the interaction between the gap and remaining balance essentially captures savings from refinancing. This finding is consistent with the mechanism proposed in Wong (2021).

Overall, results from Table 1 suggest that interactions of the gap with all other borrower characteristics have not affected the significance of the credit score interaction and only slightly changed its magnitude from 0.24 to 0.21. We conclude that credit score heterogeneity has economically significant effects on refinancing.

Our main result is robust to various sample selection and measurement issues. In Online Appendix A6, we show our results hold for the Freddie Mac 30-year FRMs, too. In Online Appendix A7, we show our result is robust to using an alternative measure of the rate gap with a lower measurement error because of borrower fixed effects. In Online Appendix A8, we show a significant credit score heterogeneity while controlling for change in the remaining balance rather than the remaining balance level. The change in the remaining balance is essentially a measure of the payment history and thus proxies the FICO score when a borrower thinks of refinancing. In Online Appendix A9, we show that our major result is robust to aggregation to quarterly frequency and 3-digit ZIP-code level.

Finally, in Online Appendix A10, we show that loose and tight monetary policies have asymmetric effects. In particular, episodes of rate decreases rather than increases, are associated with credit score heterogeneity.

2.3 Causal Effect of Rate Gaps on Refinancing

Our finding that refinance response to mortgage rates is heterogeneous across borrowers with different credit scores has important implications for monetary policy. Expansionary monetary policy increases rate gaps. Given that the relationship between rate gaps and refinancing is causal, the resulting increase in refinancing will be much higher among higher credit score borrowers than lower credit score borrowers. While the results in the previous subsection indicate a strong relationship between rate gaps and refinancing, some unobserved confounding factors might affect both rate gaps and refinance propensities even at monthly frequencies. For example, suppose household liquidity constraints negatively correlate with rate gap and refinancing (during expansions, gaps are higher, and people have more liquidity to cover refinancing costs). In that case, the OLS estimate of β has a downward bias. In this subsection, we employ the instrumental variable approach to estimate the effects of monetary policy on refinancing probability.

We re-estimate the equation (3) using a monetary policy shock as an instrument for the interest rate gap and the interaction of the shock with credit score as an instrument for the interaction of the rate gap with credit score. This approach exploits exogenous variation of rate gaps and leaves out variation because of unobserved confounding factors.

Using the high-frequency identification approach, we construct two measures of monetary policy shocks based on Federal funds futures rates, Eurodollar futures rates, and Treasury yields. To obtain the first measure of monetary shocks, we closely adhere to the methodology of Swanson (2021). The second measure of monetary shock is the change in the 2-year Treasury yield in a 1-day window around scheduled FOMC announcements.[14,15]

Table 2 displays the results from estimating equation (3) separately using OLS and IV approaches with two different instruments described above. Both

[14] See Online Appendix A11 for all the details on high-frequency shocks.

[15] See Online Appendix A12 for the first stage results.

instrumental variable specifications yield similar results in absolute magnitude and confirm that OLS estimates have a downward bias. Column (4) suggests that the marginal impact of a 50-point credit-score-increase is 0.37 percent, which amounts to 27% of the average monthly refinancing rate of 1.35 percent.

Results of this subsection imply that while expansionary monetary policy increases refinancing propensities for all borrowers, it disproportionately affects borrowers with higher credit scores. A one-percentage-point increase in the rate gap increases the probability of refinancing by 1.45 percentage points for borrowers with a credit score of 800 but only 0.72 percentage points for borrowers with a credit score of 700. Therefore, in response to monetary expansion, refinancing probability increases two times more for borrowers with a FICO credit score of 800 than borrowers with a FICO score of 700.

2.4 Potential Reason behind Refinancing Heterogeneity

In this subsection, we show that the potential reason behind lower refinancing among lower credit score borrowers is credit constraints.

Results from the previous subsection cannot differentiate between demand and supply explanations consistent with our main finding. For example, the reason behind the refinancing heterogeneity could be that higher credit score borrowers are more attentive to interest rates. Or banks might transmit lower rates only to higher credit score borrowers.

To differentiate between demand and supply explanations behind refinancing heterogeneity in credit scores, one would need to observe applications by different credit score borrowers. By narrowing the analysis to attentive borrowers who applied for a refinance loan, we can see if financial institutions prevent borrowers with lower credit scores from refinancing.

While HMDA data has information on applications for different mortgages, it does not contain information on applicants' FICO scores. Since heterogeneity results hold not only at individual but also at more disaggregated levels, we get MSA-level credit scores at origination using the Fannie Mae dataset. We treat them as proxies for the average credit score of applicants in an MSA. Then, we merge it with the refinancing loan rejection rates by MSA from the HMDA dataset.

In the HMDA dataset, we limit our analysis to single-family mortgage applications for refinancing. We define the rejection rate in an MSA as the ratio between the number of loans in an MSA for which an underwriter denied an application and the total number of loans in an MSA. The latter is a sum of loans for which a loan was originated; the application was approved but not accepted; the application was denied; the applicant withdrew the application, or the file was closed for incompleteness.

The first column in Table 3 shows the correlation between refinance loan rejection rates and credit scores in an MSA for each year from 2004 to 2019. Correlations are significantly negative throughout our sample, suggesting that rejection rates for refinancing were higher in MSAs where borrowers had lower credit scores.

In the second and third columns of Table 3, we provide correlations between refinance loan rejection rates and DTIs and LTVs. While these correlations are significant, they are lower in magnitude than the correlation with credit scores starting from 2007, implying that credit score was a relatively more important criterion for refinance loan origination than DTI or LTV.

3 Model of Refinance

Since we do not observe borrowers' spending and wealth, we infer them from a heterogeneous agent refinancing model. We show that (i) credit score heterogeneity matters for monetary transmission to aggregate consumption and that (ii) it causes long-lasting wealth and consumption- differences between credit score groups.

Our continuous-time open economy model adds credit score heterogeneity to a framework by Berger et al. (2021). Households are subject to idiosyncratic labor income risk and choose to consume or save in a liquid asset subject to a borrowing constraint, as in Aiyagari (1994). All households hold an FRM and are subject to aggregate interest rate risk. The mortgage rate in this model is a deterministic function of liquid short-term interest rates. Refinancing enters via a Calvo-style exogenous shock – households refinance at Poisson arrival times only if their rate gap is positive. The credit score determines the household's refinancing probability and the interest rate it pays for liquid debt borrowing. It can change depending on the household's mortgage payment decision.

We start by showing that credit score heterogeneity has negative aggregate implications for monetary transmission. The responses of average coupons, refinancing, and aggregate consumption to expansionary monetary shock are weaker in the heterogeneous economy than in the homogeneous one. We then decompose the aggregate consumption response to liquid wealth and refinancing channels to argue that the latter has a significant contribution to dampening the monetary transmission.

To argue that heterogeneity in credit scores has important distributional consequences, we show that the lack of refinancing opportunities contributes to wealth inequality between higher and lower credit score groups.

3.1 Model Outline

Homogeneous Economy. Each household is born at $t = 0$ with liquid savings W_0 and a house financed with a fixed-rate mortgage with constant balance F and coupon rate m_t^*. We assume households never pay down mortgages to focus only on rate incentives for refinancing and abstract from cash-out refinancing. Even though refinancing incentives arising from house price movements are significant, interest rates and resulting rate incentives respond almost immediately to monetary policy, while house prices are indirectly and more slowly affected by monetary policy.

Each mortgage can be refinanced at the discretion of the household only at random, exponentially distributed arrival times. When these opportunities arise, the household can choose to keep its existing mortgage or to refinance at the current mortgage market rate m_t for free. This setup corresponds to a Calvo model in which households get refinancing opportunities at no cost at Poisson arrival times, χ, and they exercise their option if the current market interest rate m_t is below their outstanding coupon rate m_t^*.

Households can save or borrow in liquid wealth account W_t at a rate r_t to insure against labor income shocks. The household's liability is its outstanding mortgage and payments on unsecured short-term debt if $W_t < 0$. Their net financial position is equal $W_t + r_t W_t \times \mathbb{I}\{W_t < 0\} - F$.

Finally, we assume households face the exogenous payout shocks that arrive at the Poisson rate ν, forcing them to reset their mortgage coupon to the current market mortgage rate m_t. One can interpret this feature as either a moving shock or a way to incorporate the finiteness of mortgage contracts.

Households consider two sources of uncertainty when making refinancing and consumption/savings decisions. First, they face idiosyncratic uncertainty in labor income. The second is aggregate uncertainty because the short-term interest and mortgage rates follow specific stochastic processes. [16]

Household h receives non-insurable idiosyncratic labor income Y_{ht} per unit of time, with lnY_{ht} following the continuous time Ornstein-Uhlenbeck process:

$$dlnY_{ht} = -\eta_y(lnY_{ht} - ln\bar{Y})dt + \sigma_y dZ_{ht} \tag{4}$$

where Z_{ht} is a standard Brownian motion that is independent across households, and aggregate states of the economy given by short rate fluctuations, $ln\bar{Y}$ is the ergodic mean of log income, σ_y^2 is the instantaneous variance (per unit of time) of log income, and η_y is the mean reversion parameter.

Households face aggregate uncertainty because short-term interest rate follows a model of interest rate by Cox, Ingersoll and Ross (1985):

$$dr_t = -\eta_r(r_t - \bar{r})dt + \sigma_r\sqrt{r_t}dZ_t \tag{5}$$

where Z_t is a standard Brownian motion, μ is the ergodic mean short-term rate, $r_t\sigma_r^2$ is the instantaneous variance per unit of time, and η_r is the mean reversion parameter.

Mortgage market interest rate m_t is the deterministic linear function of short-

[16] We assume that the idiosyncratic process is independent of the aggregate process. Relaxing this assumption will reinforce our conclusions through an indirect effect of monetary policy emphasized in HANK literature.

term interest rate r_t:

$$m_t = \alpha_0 + \alpha_1 r_t \tag{6}$$

Thus, fluctuations in $m_t = m(r_t)$ arise from movements in r_t in equilibrium.[17]

Note that the homogeneous economy incorporates heterogeneity in wealth, outstanding mortgage rate, and income. However, in what follows, we will use the term "heterogeneous economy" to refer to the economy with credit score heterogeneity on top of all these sources.

Heterogeneous Economy. The major difference between the homogeneous economy and the heterogeneous one is the heterogeneity in credit scores. Each household h has a credit score CS_{ht} per unit of time. Credit score impacts households across (i) refinancing opportunities and (ii) liquid assets borrowing rate. Intuitively, the borrowers' credit scores predict how likely they are to repay a loan. If this likelihood is low, they can neither refinance nor borrow more in liquid assets.

Difficulties in refinancing for households with lower credit scores are reflected in the lower Calvo shock arrival rate, χ_{CS}. Difficulties in short-term borrowing enter the model through a higher borrowing rate $r_t + r^{CS}$, with $r^{CS} > 0$ for the low credit score borrowers. The savings rate for the latter is the same as for other groups and equal to r_t.

We introduce the credit score evolution via a combination of an endogenous consumer choice and a random process. At each t, households face a choice: to miss the mortgage payment or keep up with it. If they miss the payment, their credit score decreases, and they might default with a constant probability λ. In the event of default, they experience a loss in their liquid wealth. If the household makes the mortgage payment, their credit score evolves according to an Ornstein-Uhlenbeck process

$$dCS_{ht} = -\eta_{CS}(CS - \bar{CS})dt + \sigma_{CS} dZ_{ht} \tag{7}$$

where Z_{ht} is a standard Brownian motion, $\bar{CS}$ is the ergodic mean of credit score,

[17] We abstract from redistribution between borrowers and lenders and focus on partial equilibrium outcomes because lenders have much lower MPCs than borrowers, significantly decreasing the impact of their returns on aggregate outcomes. Additionally, we assume mortgage rates do not depend on credit scores to highlight the effect of credit scores beyond mortgage rates.

σ^2_{CS} is the instantaneous variance (per unit of time), and η_{CS} is the mean reversion parameter.

To sum up, the model aims to provide a framework for analyzing the FRM refinancing channel of monetary policy transmission in the presence of credit score heterogeneity. Our partial equilibrium model has five state variables (W_h, r, m^*_h, Y_h, CS_h). Liquid wealth W and stochastic income Y introduce uninsurable income risk and wealth heterogeneity. Outstanding mortgage rate m^* introduces a refinancing motive. Time-varying interest rates r provide a role for monetary policy. Credit score CS introduces differential refinancing probabilities and short-term borrowing rates.

3.2 Household Problem

Households with identical constant relative risk aversion preferences with the rate of time preference δ and inter-temporal rate of substitution $1/\gamma$ make consumption $\{C_t\}_{t\geq 0}$, refinancing $\{\rho_t\}_{t\geq 0}$, and mortgage payment decision $\{\rho^{\text{pay}}_t\}_{t\geq 0}$ by solving the following problem:

$$\max_{C,\rho,\rho^{\text{pay}}} \mathbb{E}_0 \left[\int_0^\infty e^{-\delta t} \frac{C_t^{1-\gamma}}{1-\gamma} dt \right]$$

subject to

$$\begin{aligned} dW_t = (Y_t - C_t + r_t W_t + r^{CS} W_t \times \mathbb{I}\{W_t < 0\} - m^*_t F \times \mathbb{I}\{\text{pay}\}) dt \\ - (\underline{w} - W_{t-}) \times (1 - \mathbb{I}\{\text{pay}\}) \times dN_t^{(\tau_{\text{def}})} \end{aligned} \tag{8}$$

$$W_t \geq \underline{w} \tag{9}$$

$$dm^*_t = (m_t - m^*_{t-}) \left[\rho_t dN_t^{\left(\tau^{CS}_{\text{refi}}\right)} + dN_t^{(\tau_{\text{move}})} \right] \tag{10}$$

$$\begin{aligned} dCS_t = \left[-\eta_{cs}(CS - \bar{CS}) dt + \sigma_{cs} dZ_t \right] \times \mathbb{I}\{\text{pay}\} \\ + (\underline{CS} - CS_{t-}) \times (1 - \mathbb{I}\{\text{pay}\}) dN_t^{(\tau_{\text{nopay}})} \end{aligned} \tag{11}$$

and Y_t following (4), r_t following (5), and m_t following (6). Here τ_{refi}^{CS} is the sequence of times when refinancing shock arrives to a household with credit score CS, τ_{move} is the sequence of times the household is forced to move, and τ_{def} is the sequence of times when the household defaults. $N_t^{(\tau_{\text{refi}}^{CS})}$, $N_t^{(\tau_{\text{move}})}$, and $N_t^{(\tau_{\text{def}})}$ correspond to changes in the corresponding counting processes.

Equation (8) governs the evolution of wealth. Household receives labor income Y_t subject to uninsurable shocks, consumes, saves at short-term rate r_t, borrows debt at short-term rate $r_t + r^{CS}$. If the household pays mortgage debt, it pays an outstanding coupon on the FRM $m_t^* F$. If it misses the payment, it might default, which results in the loss of liquid wealth down to the lowest possible level of $\underline{w}$.[18]

Equation (9) is a borrowing constraint on short-term debt. Note that we do not impose different borrowing constraints for different credit score groups. Instead, borrowing is harder for lower credit score borrowers, which is reflected in the additional borrowing cost of r^{CS} in (8).

Equation (10) implies that changes in m_t^* occur either due to the refinancing shock, given that the current market mortgage rate is lower than the household's outstanding rate, or because of the moving shock. The probability of the refinancing shock arrival differs across credit score groups.

Finally, equation (11) shows the credit score evolution. If the household makes a mortgage payment, the credit score evolves according to the mean-reverting process following (7). However, the credit score will be demoted to the lowest possible level $\underline{CS}$ if the household misses the payment. See Online Appendix A13 for the details on the model solution.

3.3 Calibration

In this subsection, we describe the model's calibrated parameters. We summarize parameters in Online Appendix A14. Table A11 shows the exogenous parameter choices, while Table A12 provides refinancing and borrowing parameters.

[18] In our setup, $\underline{w} < 0$. Thus, in the case of default, borrowers would need to borrow extra funds to move to another house. We experimented with setting the wealth of households that default to zero instead of $\underline{w}$ while still allowing other households to borrow. All theoretical results were qualitatively and quantitatively indistinguishable across these specifications.

Our income calibration follows Floden and Lindé (2001), who estimate the mean reversion parameter $\eta_y = 9.3$ percent (corresponding to a half-life of 7.3 years), conditional volatility $\sigma_y = 21$ percent, and an ergodic mean log income of $E[Y_t]$=\$69,560 per year, consistent with average US household income in 2019.

We view r_t as a short-term interest rate and assume that the monetary authority adjusts these short rates. We estimate the mean reversion and volatility of the rate process with maximum likelihood estimation using daily data for 3-month treasury yields from 2000 to 2019 and get $\eta_r = 28$ percent (corresponding to a half-life of 2.48 years) and $\sigma_r = 7$ percent. Given η_r and σ_r, we then set the ergodic mean of the process to $\bar{r} = 3$ percent so that the corresponding initial model implied mortgage rate at the mean is equal to its empirical counterpart in the last quarter of 2019. See Online Appendix A15 for details on GMM estimation.

We calibrate the linear function parameters, α_0 and α_1, that relate market mortgage rates and short-term rates by regressing the mean mortgage rate on 3-month treasury yields from 2000 to 2019.

We set the coefficient of relative risk aversion γ equal to 2, which is a standard calibration in the consumption-savings literature. We fix the mortgage balance F to the average in our data of \$225,000.

Discount parameter δ is calibrated to match the mean wealth (excluding home equity) of homeowners in 2019 from the Survey of Income and Program Participation data. The primary homeowners for our sample period are Generation X and Baby Boomers. We weigh their wealth according to population shares from the Census. This strategy requires δ=10 percent per annum and generates an ergodic average liquid savings $E[W_t]$= \$ 75,200.

We calibrate the annual moving rate ν to 8.4 percent to match the empirical refinancing hazard for mortgages with negative rate gaps. In the baseline model without credit score heterogeneity, we set χ=27 percent, which implies an average monthly refinancing frequency from 2000 to 2019 of 2 percent.

We assume that credit score CS takes three values, which we call low, medium, and high: $CS \in \{L, M, H\}$. We set $\chi_L = 0$ percent, restricting households with the lowest credit score group from refinancing. $\chi_M = 26$ percent, matching the average refinancing rate for borrowers with positive rate gaps and FICO score below 75^{th}

percentile in data. We set $\chi_H = 50$ percent so that the average refinancing rate is 27 percent, equal to the average refinancing rate in data.

We calibrate the arrival rate of default to households who missed the mortgage payment $\lambda = 60$ percent so that it generates an annual default probability of 1.56%, close to 1.5% in Ganong and Noel (2020) and De Girogi and Naguib (2023).

When calibrating the credit score process parameters and spread between borrowing and saving rates for low credit score borrowers, we target the distribution of credit scores in the data.

We set the mean reversion of the credit score process to $\eta_{CS} = 8.84$ percent, corresponding to a half-life of 7.84 years.[19] We set the volatility of the credit score process using our data and obtain $\sigma_{CS} = 50$ FICO points. Given η_{CS} and σ_{CS}, we then set the ergodic mean of the process to $\bar{CS} = 750$ FICO points so that the corresponding initial model implied mortgage rate at the mean is equal to its empirical counterpart in the last quarter of 2019 when we start our experiments.

We set the difference between short-term borrowing and savings rates for the low credit score group to $r^L = 12$ p.p. For high and medium credit score groups, we set this spread equal to zero: $r^M = 0, r^H = 0$.[20] A 12 p.p. difference between the low and other credit score groups is consistent with the difference in the total cost of credit between subprime and superprime borrowers in the 2019 Consumer Credit Card Market Report by the Bureau of Consumer Financial Protection.

Note that ergodic credit score distribution depends on joint calibrations of the random process for credit score evolution and borrowing-saving spreads and the way we model the endogenous choice to miss payments. In our setup, high and medium credit score groups always pay back their mortgage, while households in the low credit score group sometimes miss their mortgage payments, with 12% of them choosing to miss the payment on average.

[19] De Girogi and Naguib (2023) show that a soft default causes a drop in the credit score by around 80 FICO points on impact, reducing to -20 points 5-6 years after the event.

[20] Note that to make the homogeneous economy and the heterogeneous economy comparable, we introduce a similar wedge between borrowing and saving rates in the homogeneous economy to make average rate differences identical across them.

3.4 Steady State

Table 4 summarizes the model's steady state which features cross-sectional heterogeneity in four variables: CS, W, m^*, and Y. Average consumption is comparable across the two economies and is less than the average income due to debt repayment. The baseline economy and the heterogeneous economy feature the same MPC out of liquid wealth equal to 0.092. Households in the low credit score group have the highest MPCs with an average of 0.105, whereas these numbers are 0.091 and 0.086 for medium and high credit score groups. The final two rows summarize the accumulation of liquid wealth. In the baseline economy, 8.3% of households are at their borrowing limit. In the heterogeneous economy, this number is 9.9%. The number of constrained households differs across credit score groups. The lowest credit score group has 16.4% of constraint households, while medium and high credit score groups have 7.3% and 8.9%, respectively.

Figure 4 summarizes ergodic distributions of wealth and coupon rates for the homogeneous economy and all the credit score groups in the heterogeneous economy. As seen from the left panel, our model endogenously generates an intuitive connection between credit scores and liquid wealth. On the one hand, a large share of households with low credit scores are trapped at lower wealth levels, mainly due to the non-zero probability of default. On the other, households with medium and high credit scores generally have more liquid savings. This difference is due to a precautionary saving motive – the cost of being financially constrained in the heterogeneous economy is higher than in the homogenous economy.

From the right panel of Figure 4, we observe that households in low credit score groups have mortgage rate distributions closer to the market mortgage rate distribution (dashed black line). In contrast, households with high credit scores concentrate at lower rates. The disparity between the groups depends on the differences in refinancing probabilities and the degree of mobility between groups. An increase in differences in refinancing probabilities moves the distributions of different groups further apart. An increase in mobility between groups neutralizes the refinancing disparities and moves the groups closer together.

The left panel of Figure 5 shows that households with low credit scores have much higher MPCs out of liquid wealth both at the borrowing limit and the zero wealth point. Households know that once they have to borrow despite having a low credit score, they could be forced to miss their mortgage payments.

As shown in the right panel of Figure 5, all groups in the heterogeneous economy have a lower MPC out of the mortgage rates than households in the homogeneous economy. Low MPCs for the low credit score group are associated with some consumers choosing to skip mortgage payments. Those who do so will be unaffected by any changes in coupon rates. This effect is more substantial for consumers with higher coupon rates because more of them choose to skip mortgage payments. However, this effect is not of primary importance for the aggregate results because very few consumers choose to miss payments.

Unlike the low credit score group, high and medium credit score groups experience lower MPCs both out of liquid wealth and out of the coupon rates than in the homogenous economy. Since these groups never miss mortgage payments, they have a higher motive for precautionary savings. Therefore, lower MPCs of these groups drive aggregate results.

3.5 Monetary Policy

In this subsection, we study the impact of expansionary monetary policy on average coupons, refinancing, and consumption in economies with and without credit score heterogeneity. Our main experiment compares impulse response functions (IRFs) of the homogeneous economy and the heterogeneous economy under cross-sectional distribution generated by the actual distribution of the outstanding mortgage rates from 2019.[21] We look at the IRFs to a one-percentage-point (100bps) cut in initial interest rate from $\bar{r}$, which causes mortgage rates to decrease by 43bps on impact.

Figure 6 compares the IRFs of average coupons (left panel), aggregate refinance (middle panel), and aggregate consumption (right panel) in the homogeneous economy (orange) and the heterogeneous economy. The average coupon of outstanding mortgages responds to monetary policy more strongly in the ho-

[21] For the IRFs under ergodic distribution, see Online Appendix A16.

mogeneous economy. This difference is due to the self-selection of households with lower credit scores into the higher interest rate gaps in the steady state we discussed in the previous section. While all the consumers can refinance in the homogeneous economy, in the heterogeneous economy, households with low credit scores remain locked in high rates. However, they would have benefited from refinancing the most.

The middle and right panels of Figure 6 show how average coupon differences translate into differences in refinancing and consumption. Average refinancing rates in the homogeneous economy and the heterogeneous economy are calibrated to be the same. However, refinance responses are smaller in the economy with credit score heterogeneity due to the differences in the initial coupon distribution discussed above.

There are substantial differences between aggregate consumption responses in the homogeneous economy and the heterogeneous one. The aggregate consumption increase in the heterogeneous economy is 23% lower on impact and 51% lower after two years.

In our setup, monetary policy affects household consumption through two channels, which we refer to as the Euler channel and the refinancing channel. The Euler channel is the standard liquid wealth effect: the cut in interest rate decreases the return on wealth for all agents and makes short-term borrowing cheaper. The refinancing channel stems from the fact the interest rate cut provides higher credit score households with the refinancing option. That allows them to reset their mortgage rate to a lower one and free up disposable income for additional consumption.

To disentangle Euler and refinancing channels of spending from each other, we proceed as follows. First, we solve the homogeneous model with refinancing to generate the initial distribution of household states. Second, we solve for a new policy function in which the transition matrix for refinancing is set to zero. The refinancing channel is then the difference between solutions in steps one and two. Finally, we repeat the same steps for the heterogeneous model.

In Figure 7, we decompose the consumption response into these two channels. Solid black and dashed black lines show the impact of the Euler channel in the homogeneous economy and the heterogeneous one. Colored lines demonstrate the effects of the refinancing channel in the homogeneous economy and the heterogeneous economy. The peak consumption response through the refinancing channel occurs three years after the shock and is equal to 35 bps in the homogeneous economy. At the same time, it is only 26 bps in the heterogeneous economy, resulting in a 33 % difference.

The effects of the two channels have very different time profiles. The impact of the Euler channel comes "on-impact" right at the time of the shock but is short-lived, hitting zero after two years and reversing later due to a negative impact on wealth. On the other hand, the effect of the refinancing channel does not arrive instantly; instead, it is longer lasting and does not wear off even after five years. Even though the refinancing activity increases on impact (see the middle panel of Figure 6), it takes more time for the significant benefits to arrive, as smaller monthly payments lead to the accumulation of wealth.

The response from the refinancing channel is lower in the heterogeneous economy due to two main effects. First, there are low credit score households that are cut off from refinancing opportunities and cannot claim the benefits of lower mortgage rates. Second, the presence of credit score heterogeneity leads to a higher precautionary motive and brings down the MPCs out of mortgage rates. Intuitively, the relative importance of the no-refinancing and MPC effects depends on the initial distribution of coupon rates. If coupon rate distributions of high and low credit score groups are closer to each other, the MPC effect accounts for a larger share of the response from the refinancing channel. If these coupon rate distributions are further apart, the no-refinancing effect becomes stronger.

3.6 Monetary Policy Disparities

In this subsection, we turn to the distributional consequences of monetary transmission in the presence of credit score heterogeneity. We initialize the heterogeneous model using the 2019 distribution of coupons by credit score group. After documenting disparities between low and higher credit score groups, we discuss a policy that smooths out these imbalances.[22]

We start our redistribution analysis in Figure 8, where we decompose the IRFs of average coupon and refinance from Figure 6 by credit score group. Note that the low credit score group cannot refinance by construction. However, IRFs for average coupon and refinance are not zero because, conditional on keeping up with mortgage payments, households can move to higher credit score groups.

To explore how this heterogeneity in refinancing opportunities affects households, in Figure 9, we provide the refinancing channel portion of wealth (left panel) and consumption (right panel) responses. The wealth of all the credit score groups increases due to mortgage refinancing. However, the low credit score group experiences a much lower rise in their wealth than other groups. They cannot refinance their mortgage and end up paying higher coupons every month. This effect accumulates over time, contributing to wealth inequality. At its peak, which occurs 14 years after the shock, the increase in the wealth of the low credit score group is 28%. For the high credit score group, after 14 years, this number is 46%, which is almost 50% higher.

Heterogeneity in refinancing contributes to consumption inequality as well. The peak response of the low credit score group's consumption is 20%, occurring 4.5 years after the shock. For the high credit score group, the corresponding number is 30%, resulting in a 40% difference between the groups.

To smooth out these disparities in wealth and consumption, one would need a policy that addresses heterogeneity in refinancing while keeping delinquency rates low. To discuss the consequences of such a policy, we consider monetary transmission a counterfactual economy that preserves credit score heterogeneity but allows the low credit score group to refinance at the same rate as the medium one.

In Figure 10, we provide IRFs for the heterogeneous model we employed before along with those for the economy where $\chi_L = \chi_M$. Average coupons and refinance responses of the low credit score group are larger in magnitude than those of the medium one and very close to those of the high group. This is so because a much larger proportion of households in the low credit score group have an incentive to

[22]For results using the ergodic density as the initial distribution, see Online Appendix A17.

refinance than in the medium group.

In the economy where low credit score group refinances at a higher rate, the wealth and consumption disparities significantly shrink, as shown in Figure 11. The debt delinquency rates decrease, both on the aggregate and for each credit score group. The increasing refinancing opportunities allow consumers to take advantage of lower rates, decrease their mortgage costs, and make it less attractive to skip payments.[23]

4 Conclusion

We have shown that credit score heterogeneity in the refinancing probability dampens monetary policy transmission through FRMs and creates long-lasting wealth differences between credit score groups.

Using Fannie Mae Single-Family Loan-Level historical data, we found that the effect of monetary policy on refinancing is heterogeneous across the borrower credit constraints. In particular, a 1% expansionary monetary policy shock causes a 1.09pp average increase in the probability of refinance, with one standard deviation increase in the credit score corresponding to a 0.37pp rise in the refinancing probability.

Our refinancing model implies that the heterogeneity of credit score dampens the consumption response to monetary policy through the FRM channel by one-third three years after the shock. The intuition behind this finding is that households with the highest benefits from refinancing cannot refinance due to their low credit scores.

Moreover, this heterogeneity creates long-lasting and economically significant wealth disparities. We estimate that 14 years after the shock, the wealth increase of the high credit score group is 50% more than that of the low credit score group. Allowing the low credit score group to refinance at the same rate as the high group smooths these disparities while not affecting delinquency rates.

To sum up, credit score heterogeneity is another significant source of monetary policy heterogeneity besides mortgage rate heterogeneity. If the mortgage

[23] For the IRFs of delinquency rates, see Online Appendix A18.

rate heterogeneity reflects the difference in refinancing gains, credit score heterogeneity implies differences in borrowing constraints. Our findings shed light on monetary policy efficiency.

References

Achdou, Yves, Francisco J. Buera, Jean-Michel Lasry, Pierre-Louis Lions, and Benjamin Moll, "Partial differential equation models in macroeconomics," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 2014, *372* (2028), 20130397.

Aiyagari, S. Rao, "Uninsured Idiosyncratic Risk and Aggregate Saving," *The Quarterly Journal of Economics*, 1994, *109* (3), 659–684.

Amromin, Gene, Neil Bhutta, and Benjamin J. Keys, "Refinancing, Monetary Policy, and the Credit Cycle," *Annual Review of Financial Economics*, 2020, *12* (1), 67–93.

Auclert, Adrien, "Monetary Policy and the Redistribution Channel," *American Economic Review*, June 2019, *109* (6), 2333–67.

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra, "Regional Heterogeneity and the Refinancing Channel of Monetary Policy," *The Quarterly Journal of Economics*, September 2018, *134* (1), 109–183.

Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra, "Mortgage Prepayment and Path-Dependent Effects of Monetary Policy," *American Economic Review*, September 2021, *111* (9), 2829–78.

Bhutta, Neil and Benjamin J. Keys, "Interest Rates and Equity Extraction during the Housing Boom," *American Economic Review*, July 2016, *106* (7), 1742–74.

Cox, John C., Jonathan E. Ingersoll, and Stephen A. Ross, "A Theory of the Term Structure of Interest Rates," *Econometrica*, 1985, *53* (2), 385–407.

DiMaggio, Marco, Amir Kermani, and Christopher J Palmer, "How Quantitative Easing Works: Evidence on the Refinancing Channel," *Review of Economic Studies*, 2020, *87* (3), 1498–1528.

__ , __ , Benjamin J. Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao, "Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging," *American Economic Review*, November 2017, *107* (11), 3550–88.

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong, "State-Dependent Effects of Monetary Policy: The Refinancing Channel," *American Economic Review*, March 2022, *112* (3), 721–61.

Floden, Martin and Jesper Lindé, "Idiosyncratic Risk in the United States and Sweden: Is There a Role for Government Insurance?," *Review of Economic Dynamics*, 2001, *4* (2), 406–437.

Ganong, Peter and Pascal J Noel, "Why Do Borrowers Default on Mortgages?," Working Paper 27585, National Bureau of Economic Research July 2020.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

Girogi, Giacomo De and Constanza Naguib, "Life after (Soft) Default," Working Paper 2023.

Goodman, Laurie, Alanna McCargo, Edward Golding, Jim Parrott, Sheryl Pardo, Todd Hill, Karan Kaul, Bing Bai, Sarah Strochak, Andrea Reyes, and John Walsh, "Housing Finance At A Glance: A Monthly Chartbook, June 2019," A Monthly Chartbook, Urban Institute 2019.

Guren, Adam M., Arvind Krishnamurthy, and Timothy J. Mcquade, "Mortgage Design in an Equilibrium Model of the Housing Market," *The Journal of Finance*, 2021, *76* (1), 113–168.

Hedlund, Aaron, Fatih Karahan, Kurt Mitman, and Serdar Ozkan, "Monetary Policy, Heterogeneity, and the Housing Channel," 2017 Meeting Papers 1610, Society for Economic Dynamics 2017.

Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti, "The Mortgage Rate Conundrum," *Journal of Political Economy*, 2022, *130* (1), 121–156.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante, "Monetary Policy According to HANK," *American Economic Review*, 2018, *108* (3), 697–743.

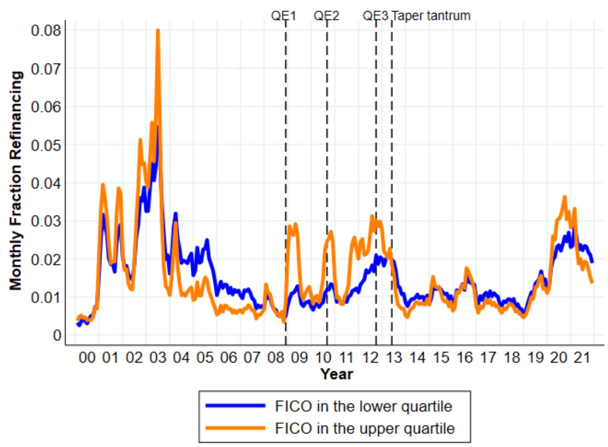
__ , Kurt Mitman, and Giovanni L. Violante, "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 2020, *128* (9), 3285–3345.

Leamer, Edward E., *Specification Searches: Ad Hoc Inference with Nonexperimental Data*, John Wiley & Sons, 1978.

Swanson, Eric T., "Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets," *Journal of Monetary Economics*, 2021, *118*, 32–53.

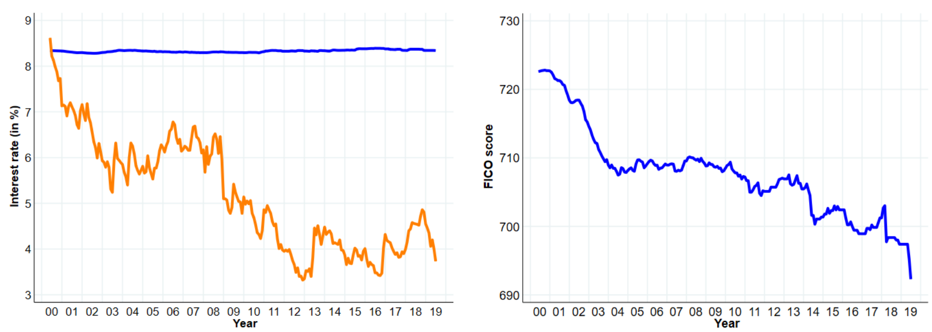
Wong, Arlene, "Refinancing and The Transmission of Monetary Policy to Consumption," Working Papers 2021-57, Princeton University. Economics Department. March 2021.

Figure 1: Unconditional Monthly Refinance Hazard for Lower- and Upper-quartile Credit Score Borrowers



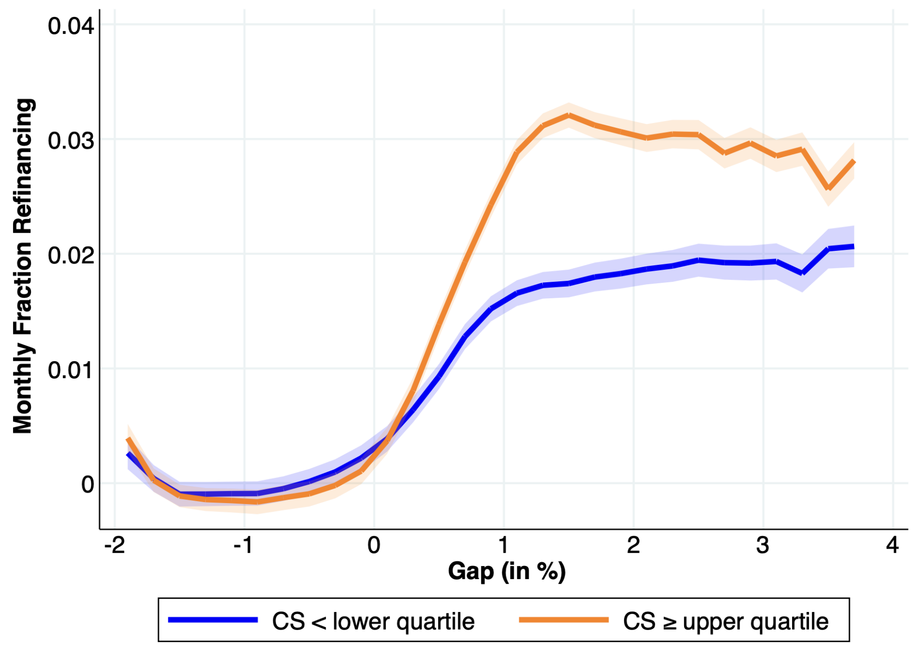
Notes: The figure shows monthly refinance hazard defined as the monthly fraction of loans that refinance. Events are QE1, the announcement of the original LSAP in November 2008; QE2, Bernanke's August 2010 speech suggesting an expansion of LSAPs; QE3, FOMC vote to buy $40b bonds per month in September 2012; Taper tantrum, Bernanke's 2013 FOMC press conference suggesting that FOMC would wind down purchases of MBS.

Figure 2: Average Mortgage Rate and Credit Score of Outstanding Mortgages Originated in 05/2000



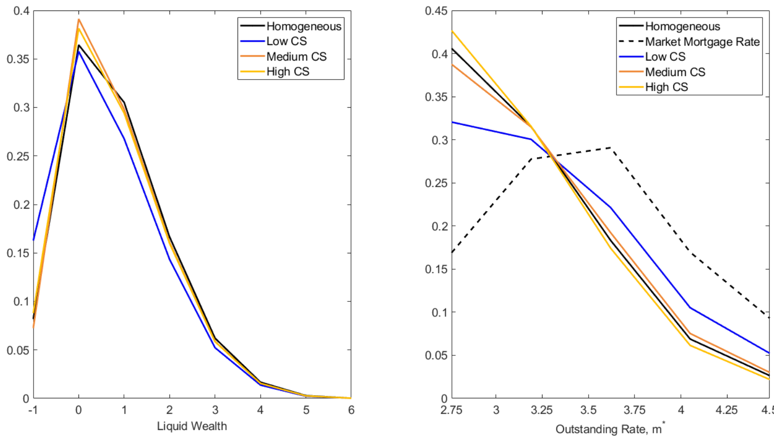
Notes: The left panels show the average outstanding mortgage rate (blue) along with the market mortgage rate (orange). The right panels show the average credit score on outstanding mortgages. The market mortgage rate comes from FRED, Federal Reserve Bank of St. Louis at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

Figure 3: Refinance Hazard with Individual Controls for Lower and Upper Quartile Credit Score Borrowers



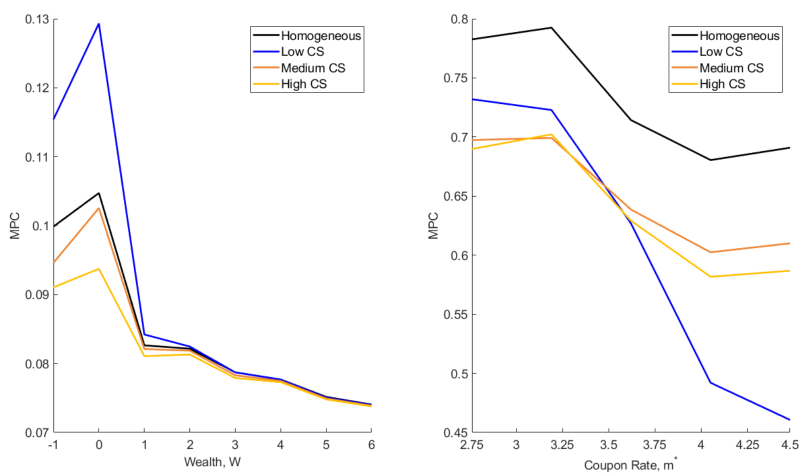
Notes: Figure shows point estimates for coefficients $\beta + \delta$ on the 20bp bin dummies in regression (2) for borrowers in the lower credit score quartile (blue) and in the upper credit score quartile (orange). Controls include a quadratic in LTV, a quadratic in DTI, a quadratic in loan age, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, and a 3-digit ZIP-code fixed effects. Standard errors are double clustered by 3-digit ZIP code and year-month.

Figure 4: Ergodic Distributions of Liquid Wealth and Coupon Rate



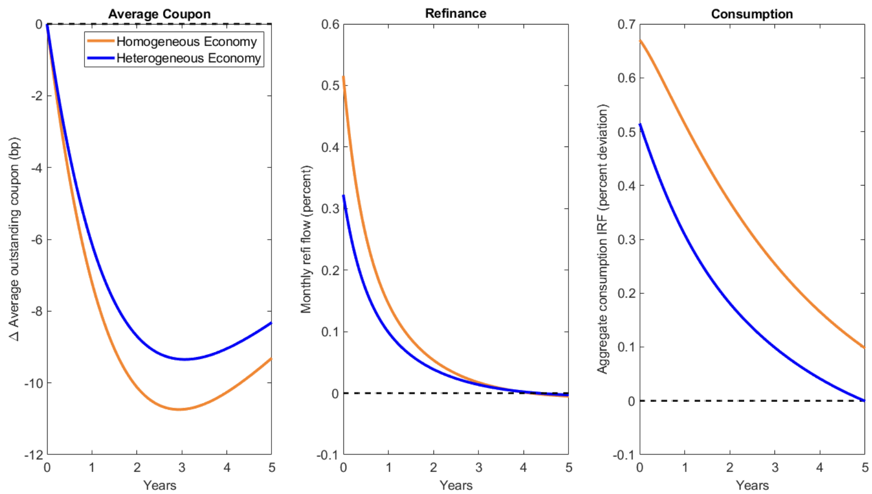
Notes: The figure shows ergodic distributions of liquid wealth (left panel) and coupon rate (right panel) of the homogeneous economy (black) and each credit score group (blue, orange, yellow) in the heterogeneous economy.

Figure 5: Marginal Propensities to Consume in Steady State



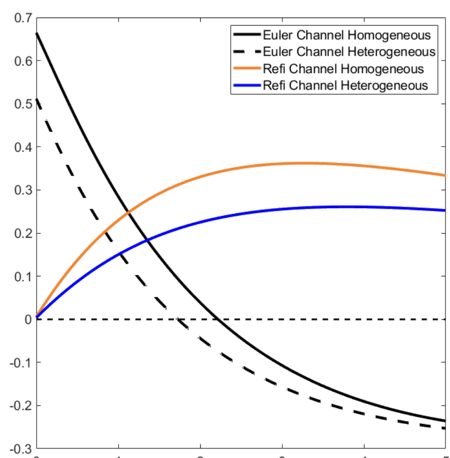
Notes: The figure shows the MPC out of the liquid wealth (left panel) and MPC out of the coupon rate (right panel) of the homogeneous economy (black) and each credit score group (blue, orange, yellow) in the heterogeneous economy. MPC is defined as the first derivative of optimal consumption with respect to the variable of interest: $MPC_x = \frac{\partial C}{\partial x}$.

Figure 6: IRFs to 100 bps Decline in r starting from the 2019 Distribution



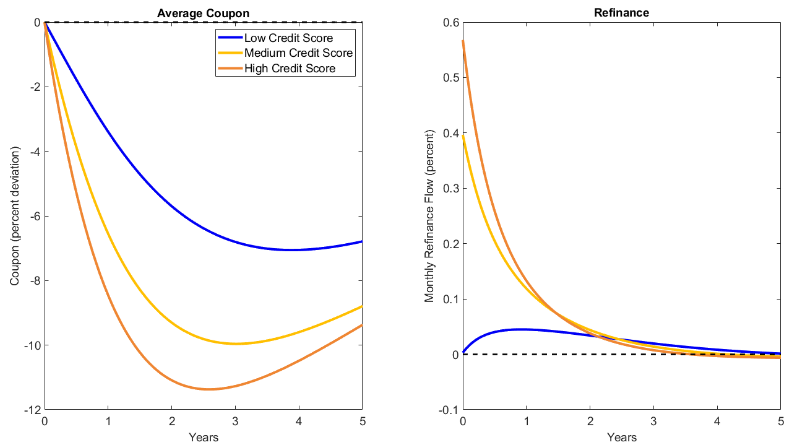
Notes: The figure shows the IRFs of average coupon (left panel), aggregate refinance (middle panel), and aggregate consumption (right panel) for the homogeneous economy (orange) and the heterogeneous economy (blue), starting from the 2019 distribution.

Figure 7: Consumption Response Decomposition



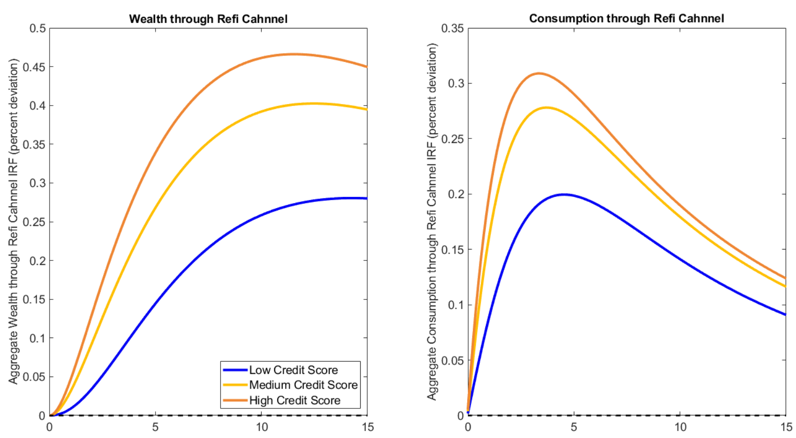
Notes: The figure decomposes the IRF of aggregate consumption into Euler (solid black and dashed lines) and refinancing (orange and blue) channels in the homogeneous economy and the heterogeneous economy, starting from the 2019 distribution. See the text for details.

Figure 8: IRFs to 100 bps Decline in r by Credit Score Group



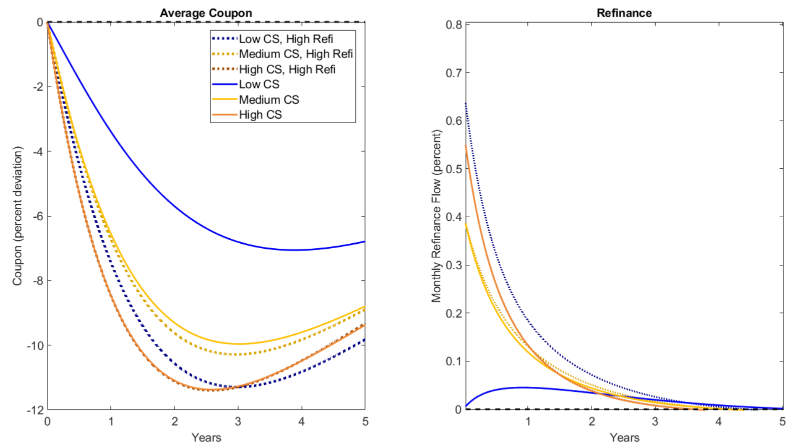
Notes: The figure shows the IRFs of average coupon (left panel) and aggregate refinance (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. See the text for details.

Figure 9: Refinancing Channel of 100 bps Decline in r by Credit Score Group



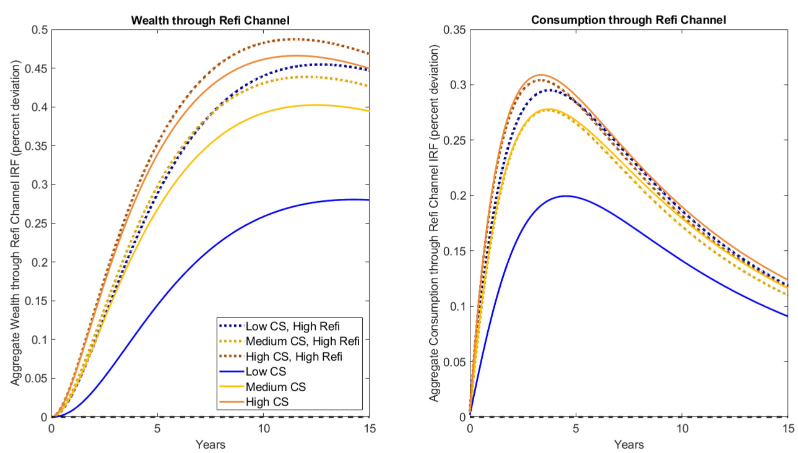
Notes: The figure shows the refinancing channel portion of the IRFs of aggregate wealth (left panel) and aggregate consumption (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. See the text for details.

Figure 10: IRFs to 100 bps Decline in *r* by Credit Score Group



Notes: The figure shows the IRFs of average coupon (left panel) and aggregate refinance (right panel) by low (blue), medium (yellow), and high (orange) credit score groups for the baseline heterogeneous economy (solid lines) and counterfactual economy (dashed line). The initial distribution corresponds to the 2019 distribution. See the text for details.

Figure 11: Refinancing Channel of 100 bps Decline in *r* by Credit Score Group



Notes: The figure shows the refinancing channel portion of the IRFs of aggregate wealth (left panel) and aggregate consumption (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. The initial distribution corresponds to the 2019 distribution. See the text for details.

Table 1: Refinance Results for Regression (3)

	(1)	(2)	(3)	(4)
gap	0.741***	0.728***	0.733***	0.865***
	(0.020)	(0.020)	(0.020)	(0.027)
CS	-0.054***	-0.057***	-0.054***	-0.035***
	(0.007)	(0.007)	(0.007)	(0.007)
gap × CS	0.238***	0.243***	0.237***	0.212***
	(0.006)	(0.007)	(0.007)	(0.006)
LTV	-0.228***	-0.250***	-0.253***	-0.242***
	(0.013)	(0.013)	(0.013)	(0.012)
DTI	0.011	0.011	0.028***	0.036***
	(0.004)	(0.004)	(0.003)	(0.004)
rem. balance	0.454***	0.454***	0.455***	0.353***
	(0.022)	(0.022)	(0.022)	(0.013)
gap × LTV		0.032**	0.037***	-0.026
		(0.007)	(0.007)	(0.011)
gap × DTI			-0.038***	-0.073***
			(0.003)	(0.004)
gap × rem. balance				0.498***
				(0.020)
# of borrowers	0.090***	0.089***	0.090***	0.078***
	(0.007)	(0.007)	(0.007)	(0.007)
age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age × age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
age × age × age	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
constant	2.478***	2.461***	2.462***	2.438***
	(0.054)	(0.053)	(0.053)	(0.053)
Age controls	X	X	X	X
Underwriting char-s	X	X	X	X
Orig. yr-month FE	X	X	X	X
ZIP FE	X	X	X	X
Yr-month × ZIP FE	X	X	X	X
Observations	144,143,468	144,143,468	144,143,468	144,143,468
R^2	0.013	0.013	0.013	0.014

Standard errors in parentheses

* $p < .000083$, ** $p < .000042$, *** $p < .0000083$

Notes: The table reports LPM estimates of loan-level regression (3) – the likelihood of mortgage refinance on a set of mortgage characteristics at the monthly frequency. The refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration).

Table 2: OLS and IV Results Refinance Probabilities for Regression (3)

$\mathbb{1}\{\text{Refi}\}$	OLS		3-factor shock		Δ 2-year Treasury Yield	
	(1)	(2)	(3)	(4)	(5)	(6)
gap	0.565***	0.748***	1.133***	1.085***	0.923***	0.893***
	(0.022)	(0.030)	(0.175)	(0.168)	(0.170)	(0.170)
CS	-0.011	-0.057***	-0.101	-0.118	-0.089	-0.106
	(0.013)	(0.012)	(0.034)	(0.031)	(0.029)	(0.028)
gap × CS	0.212***	0.235***	0.383***	0.368***	0.381***	0.356***
	(0.009)	(0.010)	(0.053)	(0.053)	(0.051)	(0.052)
LTV		-0.230***		-0.220***		-0.225***
		(0.018)		(0.019)		(0.017)
DTI		0.018		0.021		0.018
		(0.006)		(0.007)		(0.006)
rem. balance		0.370***		0.398***		0.382***
		(0.038)		(0.044)		(0.038)
# of borrowers		0.101***		0.106***		0.104***
		(0.011)		(0.012)		(0.011)
age	0.067***	0.066***	0.059***	0.062***	0.062***	0.064***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
age × age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age × age ×age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age controls	X	X	X	X	X	X
Underwriting characteristics		X		X		X
ZIP FE	X	X	X	X	X	X
Orig. year-qrt × ZIP FE	X	X	X	X	X	X
Observations	88,356,649	79,762,158	88,356,649	79,762,158	88,356,649	79,762,158
R^2	0.012	0.012	0.001	0.002	0.001	0.002

Standard errors in parentheses

* $p < .00011$, ** $p < .000056$, *** $p < .000011$

Notes: The table reports OLS and IV LPM estimates of loan-level regression (3). See text for details on instruments.

Table 3: Correlation between Refinance Loan Rejection Rates for Borrower Characteristics

year	CS	DTI	LTV
2004	-0.378***	-0.103*	0.631***
2005	-0.160***	-0.290***	0.643***
2006	-0.186***	-0.260***	0.561***
2007	-0.415***	0.05	0.313***
2008	-0.310***	0.147***	0.078
2009	-0.339***	0.444***	-0.009
2010	-0.324***	0.264***	-0.015
2011	-0.307***	0.239***	0.068
2012	-0.479***	0.198***	0.143***
2013	-0.423***	0.097*	0.159***
2014	-0.253***	0.047	0.108**
2015	-0.331***	0.042	0.150***
2016	-0.319***	0.102**	0.246***
2017	-0.301***	-0.076	0.188***
2018	-0.283***	0.157***	0.055
2019	-0.342***	0.047	0.267***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the time series of correlation between rejection rates for refinance loans and borrower characteristics at the MSA level. The rejection rates are from the HMDA dataset, and the borrower characteristics are from the Fannie-Mae Single-Family Loan-Level historical dataset.

Table 4: Steady State Summary Statistics

	Baseline Economy	Heterogeneous Economy			
		Low	Medium	High	Total
Average consumption ($)	55,134	50,381	56,017	56,190	54,869
Average MPC out of wealth	0.092	0.105	0.091	0.086	0.092
Share of constrained households	8.3%	16.4%	7.3%	8.9%	9.9%
Share of households with $W \leq 0$	44.7%	52.2%	46.5%	9.1%	47.1%

Notes: The table summarizes household consumption, expenditure, and saving behavior in the steady state.

FOR ONLINE PUBLICATION

A1 Predicted Mortgage Rate

Table A1 displays estimation results of regression (1) and shows that coefficients are consistent with previous findings reported in the literature. Borrowers with higher credit scores, lower LTV, and lower DTI ratios have lower mortgage rates. This specification explains about 90 percent of the variation in outstanding mortgage rates.

Table A1: Results for Regression (1)

	Outstanding Mortgage Rate
CS	-0.012***
	(0.000)
CS × CS	0.000***
	(0.000)
LTV	0.003***
	(0.000)
LTV × LTV	0.000***
	(0.000)
DTI	0.002***
	(0.000)
DTI × DTI	0.000***
	(0.000)
market mortgage rate	0.910***
	(0.000)
constant	5.593***
	(0.052)
Observations	3,533,488
R^2	0.897

Standard errors in parentheses

* $p < .0005$, ** $p < .00027$, *** $p < .00005$

Notes: The table reports estimates of loan-level regression (1) – the outstanding mortgage rate on a set of mortgage characteristics and market mortgage rate.

A2 Summary Statistics of the Fannie Mae Data

Table A2: Summary Statistics of the Fannie Mae Data

Panel A: Fixed Characteristics at Mortgage Origination

	Median	Mean	St. Dev.	Min	Max
Interest Rate (ppts)	4.75	4.90	1.39	1.88	12.13
Loan Amount ($100k)	2.00	2.26	0.13	0.01	15.66
LTV (%)	79.00	73.89	16.31	1.00	97.00
DTI (%)	35.00	34.53	10.85	1.00	64.00
FICO Credit Score	757.00	746.92	48.05	620.00	850.00
Refinance Loan	1.00	0.54	0.50	0.00	1.00
Purchase Loan	0.00	0.46	0.50	0.00	1.00
Rate Refinance Loan	0.00	0.30	0.46	0.00	1.00
Cash-out Refinance Loan	0.00	0.24	0.43	0.00	1.00
Number of loans			3,580,928		

Panel B: Time-Varying Characteristics

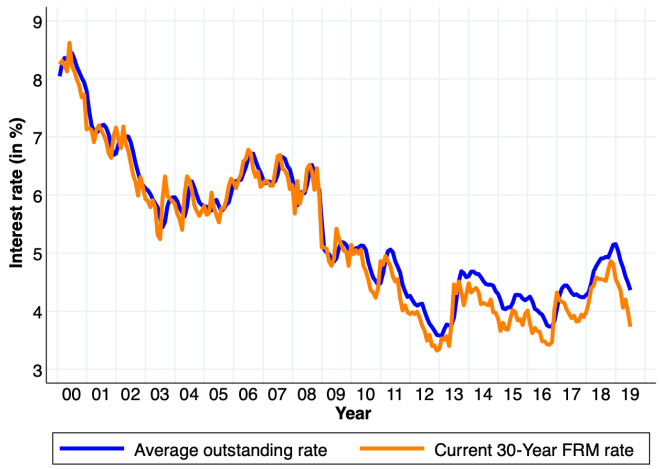
	Median	Mean	St. Dev.	Min	Max
Loan Age (months)	31.00	42.31	39.07	1.00	263.00
Interest Rate (ppts)	5.00	5.08	1.19	1.88	12.13
Remaining Balance ($100k)	1.59	1.85	1.10	0.00	15.66
LTV (%)	65.77	64.38	21.83	0.00	156.31
Refinance (ppts)	0.00	1.53	12.29	0.00	100.00
Number of loan-months			149,070,748		

Notes: The table shows summary statistics from a 10% random sample of fully amortizing, full documentation, single-family, conventional 30-year FRM acquired by Fannie Mae between January 1, 2000, and March 31, 2019. The unit of observation in Panel A is a loan, while a loan-month in Panel B. Refinance Loan, Purchase Loan, Rate Refinance Loan, Cash-out Refinance Loan, and Refinance are dummy variables.

A3 Mortgage Sample Representativeness

We treat our sample as representative of the population - the mean mortgage rate for contracts in our sample heels the monthly average of all 30-year FRMs.

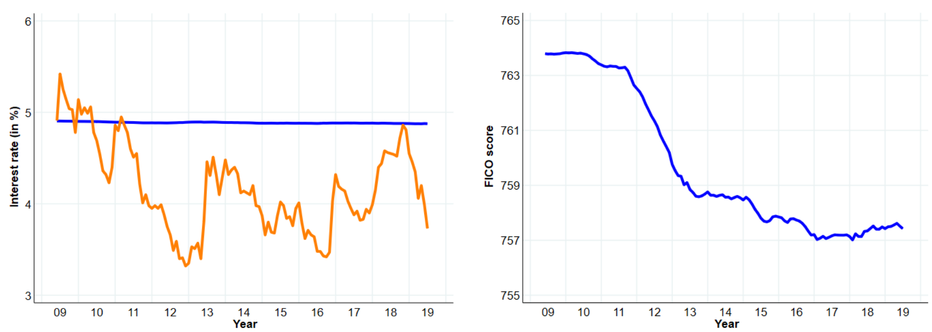
Figure A1: Average Outstanding Rate in Fannie Mae Data vs. Market Mortgage Rate (FRED)



Notes: Figure shows the average outstanding mortgage rate of the Fannie-Mae Single-Family Loan-Level historical data and the market mortgage rate from FRED, Federal Reserve Bank of St. Louis at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

A4 Mortgage Rate and Credit Score Dynamics of Cohort 05/2009

Figure A2: Average Mortgage Rate and Credit Score of Outstanding Mortgages Originated in 05/2009



Notes: The left panels show the average outstanding mortgage rate (blue) along with the market mortgage rate (orange). The right panels show the average credit score on outstanding mortgages.

A5 Baseline Refinance Results

In this section, we quantify credit score differences in the sensitivity of refinancing to gaps. We employ linear probability models and estimate them at a monthly frequency. Our regressions take the following form: for the loan i at month t, we estimate

$$\mathbb{1}\{\text{Refi}_{it}\} = \alpha + \beta gap_{it} + \gamma CS_i + \delta gap_{it} \times CS_i + X_{it}\Gamma + \varepsilon_{it} \tag{A1}$$

where $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; gap_{it} is a rate gap of household i in month t; CS_i is a credit score of household i; $CS_i \times gap_{it}$ is the interaction between credit score and rate gap of household i in month t; X_{it} denotes a vector of controls. We include geographic fixed effects and origination year-month fixed effects in some specifications. The standard errors are double-clustered on a 3-digit ZIP code and a monthly level. All variables, except the interest rate gap, were normalized around the corresponding sample means. All coefficients were multiplied by 100 to arrive at percentage changes.

We begin by quantifying credit score differences in the sensitivity of refinancing to gaps δ by running the OLS specification of equation (A1). Table A3 provides the estimation results.[24] Column (1) reports estimates from a specification without an interaction term, which includes a third-order polynomial for mortgage age (duration) and origination year-month fixed effects, which take care of changes in underwriting criteria over time. The coefficients in front of the rate gap and credit score are consistent with previous findings of the literature on the FRM channel. A one-percentage-point increase in rate gap is associated, on average, with a 0.84 percentage point higher probability of refinancing. Borrowers with one standard deviation above mean credit scores are 0.08 percentage points more likely to refinance.

Recall that we construct the rate gap using the predicted rate for each borrower

[24] Note that we adjusted significance levels of 10%, 5%, and 1% in all the tables for the sample size. According to Leamer (1978), in very large samples, we should reject the null if the test-statistic in absolute value is above $t_{cr} = \sqrt{N(N^{\frac{1}{N}} - 1)}$. Alternatively, one could adjust the significance level according to the formula $\alpha_{stan} = \alpha / \sqrt{N/100}$.

given their characteristics for FICO, OLTV, and DTI. If differences in refinancing between lower and higher credit score borrowers are because of their differential sensitivities to rate gaps, then the coefficient before the interaction term should be positive. Column (2) of Table A3 confirms this conjecture: a one-percentage-point increase in rate gap is associated with a 1.2 percentage point increase in the probability of refinancing for borrowers with a credit score of 800 (one standard deviation above mean credit score) but only a 0.64 percentage point increase for borrowers with a credit score of 700 (one deviation below mean credit score).

To determine whether differential sensitivities to the rate gap between lower and higher credit score borrowers arise because of variation in their observable characteristics, in column (3) of Table A3, we include underwriting characteristics and state fixed effects. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). Borrowers with lower LTV ratios and larger remaining balances are more likely to refinance. The sensitivity to the rate gap remains significant and slightly increases. The coefficient in front of DTI has a positive sign, suggesting that borrowers with a higher DTI ratio are more likely to refinance.

In column (4) of Table A3, we estimate differential sensitivities to rate the gap between lower and higher credit score borrowers using variation within 3-digit ZIP codes. While ZIP-code fixed effects take care of time-invariant unobserved characteristics of small geographic areas, such as demographics and average education level, they do not materially change estimates of either of the coefficients.

A6 Robustness: Refinancing Hazard for Freddie Mac Loans

In Figure A3, we provide the monthly CPR rate for the Freddie Mac Single-Family Loan-Level data. A comparison between Figure 3 and Figure A3 shows that they are very similar. In particular, both show significant differences in refinancing between lower and upper-quartile credit score borrowers.

Table A3: Baseline Refinance Results for Regression (A1)

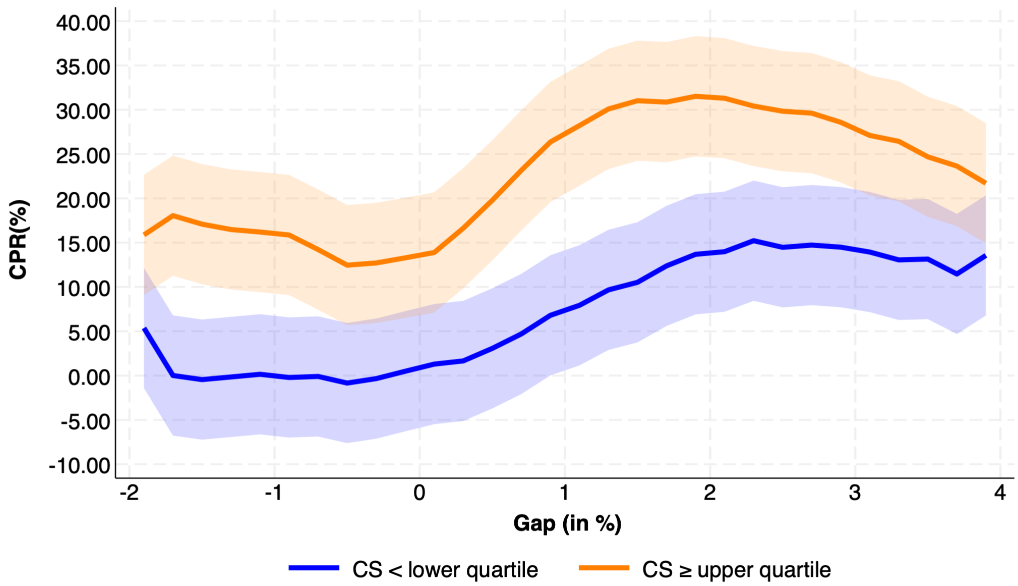
𝟙{Refi}	(1)	(2)	(3)	(4)	(5)
gap	0.843***	0.914***	1.126***	1.133***	0.741***
	(0.036)	(0.034)	(0.039)	(0.039)	(0.020)
CS	0.084***	-0.031	-0.108***	-0.113***	-0.054***
	(0.012)	(0.009)	(0.009)	(0.009)	(0.007)
gap× CS		0.272***	0.300***	0.300***	0.238***
		(0.007)	(0.009)	(0.009)	(0.006)
LTV			-0.279***	-0.295***	-0.228***
			(0.018)	(0.018)	(0.013)
DTI			0.023***	0.024***	0.011
			(0.004)	(0.004)	(0.004)
rem. balance			0.445***	0.461***	0.454***
			(0.023)	(0.023)	(0.022)
# of borrowers			0.104***	0.093***	0.090***
			(0.008)	(0.008)	(0.007)
age	0.035***	0.035***	0.035***	0.035***	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)
age × age	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age × age × age	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.829***	0.829***	0.621***	0.637***	2.478***
	(0.061)	(0.060)	(0.049)	(0.049)	(0.054)
Age controls	X	X	X	X	X
Underwriting char-s			X	X	X
Orig. yr-month FE	X	X	X	X	X
State FE			X		
ZIP FE				X	X
Yr-month × ZIP FE					X
Observations	159,043,872		144,150,179	144,150,159	144,143,468
R^2	0.005	0.006	0.008	0.008	0.013

Standard errors in parentheses

* $p < .000083$, ** $p < .000042$, *** $p < .0000083$

Notes: The table reports LPM estimates of loan-level regression (A1) – the likelihood of mortgage refinance on a set of mortgage characteristics.

Figure A3: CPR for Lower and Upper Quartile Credit Score Borrowers in Freddie Mac Data



The figure shows point estimates for coefficients $\beta + \delta$ on the 20bp bin dummies in regression (2) for borrowers in the lower credit score quartile (blue) and in the upper credit score quartile (orange). The estimation is performed using the Freddie Mac Single-Family Loan-Level historical dataset. Controls include a quadratic in LTV, a quadratic in DTI, a quadratic in loan age, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, and a 3-digit ZIP code fixed effects. Standard errors are double clustered by 3-digit ZIP code and year.

A7 Robustness: Alternative Measure of Rate Gap

In this subsection, we show that our main result is robust to using an alternative measure of the rate gap, which eliminates borrower fixed effects.

We construct rate gap, $gap_{it} = \hat{m}_{i\tau} - \hat{m}_{it}$, by calculating the difference between the predicted fixed interest rate on the outstanding loan, $\hat{m}_{i\tau}$, and the predicted rate, $\hat{m}_{it}$, for a new FRM originated in period t given borrower/loan characteristics for FICO, LTV, and DTI. Both rates are predictions from the regression (1), and $\hat{m}_{i\tau}$ is a prediction for a rate at the time of origination. The rationale behind this definition is to eliminate borrower fixed effects. For example, some borrowers might get unusually high or low interest rates for reasons unrelated to underwriting criteria.

The estimation results are provided in Table A4. Column (1) reports estimates from a specification without an interaction term, including a third-order polynomial for mortgage age (duration) and origination year-month fixed effects, which take care of changes in underwriting criteria over time. The estimates of β and δ are higher than those reported for the baseline model in Table A3. A one-percentage-point increase in this measure of rate gap is associated, on average, with a 1.26 percentage point higher probability of refinancing. Borrowers with one standard deviation above mean credit scores are 0.12 percentage points more likely to refinance.

Column (2) of Table A4 shows that a one-percentage-point increase in rate gap is associated with a 1.6 percentage point increase in the probability of refinancing for borrowers with a credit score 800, but only a one-percentage-point increase for borrowers with a credit score 700. Column (3) of Table A4 includes underwriting characteristics and 3-digit ZIP fixed effects. While the credit score sensitivity to the rate gap is higher than one from Table A3 (0.297 vs. 0.238), the relative difference between borrowers with excellent and good credit scores is smaller because this rate gap measure has a larger effect on refinancing. A one-percentage-point increase in the rate gap is associated with a 1.74 percentage-point increase in the probability of refinancing for borrowers with a credit score of 800 and a 1.15 percentage-point increase for borrowers with a credit score of 700.

A8 Robustness: Payment History

Even though the FICO credit score of a borrower is persistent, the FICO score when a borrower thinks of refinancing is more relevant for obtaining the refinance loan rather than at mortgage origination. One of the most critical determinants of the FICO score is payment history. While we do not observe repayment of other debts except the mortgage, in this subsection, we examine credit score heterogeneity

Table A4: Robustness of Regression (A1) to Using Alternative Measure of Rate Gap

	(1)	(2)	(3)
gap	1.263***	1.308***	1.443***
	(0.056)	(0.055)	(0.055)
CS	0.126***	-0.024	-0.098***
	(0.012)	(0.009)	(0.008)
gap × CS		0.295***	0.297***
		(0.008)	(0.009)
LTV			-0.360***
			(0.022)
DTI			0.009
			(0.004)
rem. balance			0.399***
			(0.021)
# of borrowers			0.086***
			(0.007)
age	0.032***	0.032***	0.031***
	(0.003)	(0.003)	(0.003)
age × age	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
age × age × age	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
constant	0.820***	0.826***	0.692***
	(0.059)	(0.058)	(0.047)
Age controls	X	X	X
Underwriting char-s			X
Orig. yr-month FE	X	X	X
ZIP FE			X
Yr-month × ZIP FE			
Observations	1.59e+08	1.59e+08	1.44e+08
R^2	0.006	0.006	0.008

Standard errors in parentheses
* $p < .000083$, ** $p < .000042$, *** $p < .0000083$

Notes: The table reports LPM estimates of loan-level regression (A1) with additional interaction terms – the likelihood of mortgage refinance on a set of mortgage characteristics.

while controlling for change in the remaining balance rather than the remaining balance level.

The estimation results are provided in Table A5. Column (1) suggests that a one-percentage-point increase in rate gap is associated with a 0.88 percentage point increase in the probability of refinancing for borrowers with a credit score of 800 and a 0.43 percentage point increase for borrowers with a credit score of 700. Including other interaction terms in column (2) does not significantly alter the results. Overall, the results from this estimation suggest the same relative difference between excellent and good credit score borrowers.

A9 Robustness: Time- and Geographical Aggregation

The micro-level evidence shows a strong relationship between rate gaps, credit score sensitivity to rate gaps, and refinancing when pooling the data across all months and all individuals. We next show that our major result is robust to aggregation to quarterly frequency and 3-digit ZIP-code level.

Table A6 is the quarterly version of Table A3. The key difference between the two is that the interest rate gaps, LTV, remaining balance, and refinance indicator are averaged quarterly (as opposed to monthly) for each borrower in our sample. All specifications include age control – third order polynomial for the number of quarters since origination and origination year-quarter fixed effects. Column (1) estimates imply that a one-percentage-point increase in rate gap is associated with a 2.1 percentage point increase in the quarterly probability of refinancing for borrowers with a credit score of 800 (one standard deviation above mean credit score) but only a 1.13 percentage point increase for borrowers with a credit score of 700 (one standard deviation below mean credit score). In column (2), we include underwriting characteristics and ZIP-code fixed effects. We again find that the refinancing differences between different credit score borrowers are more correlated with credit score rather than neighborhoods that these borrowers live in. A full set of year-quarter-by-ZIP-code fixed effects in column (3) only slightly decreases credit score sensitivity to the rate gap, from 0.49 to 0.44 in absolute magnitude.

Table A5: Robustness of Regression (A1) to Inclusion of Payment History

	(1)	(2)
gap	0.655***	0.633***
	(0.019)	(0.019)
CS	-0.036***	-0.034***
	(0.007)	(0.007)
gap×CS	0.227***	0.223***
	(0.006)	(0.006)
LTV	-0.090***	-0.111***
	(0.012)	(0.013)
DTI	0.030***	0.048***
	(0.003)	(0.003)
Δ rem. balance	-0.000***	-0.000***
	(0.000)	(0.000)
gap×LTV		0.034***
		(0.006)
gap×DTI		-0.037***
		(0.003)
gap × Δ rem. balance		-0.000***
		(0.000)
# of borrowers	0.211***	0.211***
	(0.010)	(0.010)
age	0.000	0.000
	(0.000)	(0.000)
age × age	-0.001***	-0.001***
	(0.000)	(0.000)
age × age × age	0.000***	0.000***
	(0.000)	(0.000)
constant	2.232***	2.223***
	(0.057)	(0.055)
Age controls	X	X
Underwriting char-s	X	X
Orig. yr-month FE	X	X
ZIP FE	X	X
Yr-month × ZIP FE	X	X
Observations	1.41e+08	1.41e+08
R^2	0.013	0.013

Standard errors in parentheses
* $p < .000083$, ** $p < .000042$, *** $p < .0000083$

Notes: The table reports LPM estimates of loan-level regression (A1) with additional interaction terms – the likelihood of mortgage refinance on a set of mortgage characteristics.

In Table A7, we exploit variation in rate gaps, credit score, and refinancing across ZIP codes to show that there is a strong positive relationship between rate gaps, credit score sensitivity to rate gap, and refinancing, even after including both year-month and year-month-by-ZIP-code fixed effects. Results are very similar in magnitude to the ones we got using loan-level variation. The specification with a complete set of controls in column (3) implies that the credit score sensitivity to the rate gap is 0.20, which is close to its loan-level counterpart of 0.24 from column (5) of Table A3.

Table A6: Refinance Results at Quarterly Frequency

$\mathbb{1}$\{Refi\}	(1)	(2)	(3)
gap	1.615***	2.001***	1.465***
	(0.122)	(0.142)	(0.086)
CS	-0.057	-0.195**	-0.106
	(0.040)	(0.038)	(0.030)
gap × CS	0.485***	0.536***	0.440***
	(0.025)	(0.032)	(0.026)
LTV		-0.460***	-0.303***
		(0.045)	(0.052)
DTI		0.038	0.021
		(0.018)	(0.016)
rem. balance		0.790***	0.774***
		(0.091)	(0.091)
# of borrowers		0.164**	0.159***
		(0.033)	(0.029)
age	0.229**	0.229***	0.366***
	(0.045)	(0.043)	(0.059)
age × age	-0.009**	-0.009**	-0.010***
	(0.002)	(0.002)	(0.001)
age × age × age	0.000*	0.000*	0.000***
	(0.000)	(0.000)	(0.000)
constant	1.140	0.781	-0.642
	(0.262)	(0.230)	(0.694)
Age controls	X	X	X
Underwriting char-s		X	X
Orig. yr-qrt FE	X	X	X
ZIP FE		X	X
Yr-qrt × ZIP FE			X
Observations	55,036,198	50,096,147	50,094,565
R^2	0.010	0.014	0.021

Standard errors in parentheses

* $p < .00014$, ** $p < .000071$, *** $p < .000014$

Notes: The table reports LPM estimates of loan-level regression (A1) – the likelihood of mortgage refinance on a set of mortgage characteristics at the quarterly frequency.

Table A7: Refinance with Interaction Results at ZIP-level

$\mathbb{1}$\{Refi\}	(1)	(2)	(3)
gap	-0.104	1.076***	1.267***
	(0.091)	(0.161)	(0.182)
CS	0.085*	-0.125**	-0.147***
	(0.027)	(0.035)	(0.037)
gap × CS	0.089	0.177**	0.202*
	(0.040)	(0.047)	(0.062)
LTV			-0.070**
			(0.020)
DTI			-0.014
			(0.028)
rem. balance			0.201***
			(0.047)
constant	1.469***	0.966***	0.886***
	(0.040)	(0.070)	(0.078)
Underwriting char-s			X
ZIP FE		X	X
Yr-month FE	X	X	X
Observations	237,090	237,090	228,641
R^2	0.115	0.144	0.225

Standard errors in parentheses

* $p < .0021$, ** $p < .0010$, *** $p < .00021$

Notes: The table reports LPM estimates of 3-digit ZIP-level regression (A1) – the likelihood of mortgage refinance on a set of mortgage characteristics.

A10 Tight Monetary Policy

Market mortgage rates have been chiefly decreasing over the last 20 years. To show that loose and tight monetary policy have asymmetric effects, in this subsection, we re-estimate equation (A1) during two episodes of tight monetary policy – from July 2004 to June 2006 and from December 2015 to December 2018.

Table A8 provides estimation results for two episodes of tightening monetary policy. Column (1) implies that credit score heterogeneity did not matter from

July 2004 to June 2006. This result is consistent with Amromin, Bhutta and Keys (2020), who document that borrowers with lower credit scores were more likely to refinance their mortgage to extract cash against increasing house equity caused by rising house prices.

Column (2) of Table A8 suggests that credit score heterogeneity was significant during December 2015 – December 2018 tightening cycle. Both rate gap and credit score sensitivity to the rate gap are lower than for the entire sample period. A one-percentage-point increase is associated with a 0.41 percentage-point increase in refinancing probability for the borrower with a mean FICO score of 750. The marginal effect of increasing the credit score by one standard deviation is 0.08 percentage points.

A11 Construction of Monetary Policy Shocks

We use high-frequency measures of monetary policy shock. High-frequency identification controls the market expectations by considering changes in the target rate within a small window and, thus, overcomes two empirical challenges in identifying the effect of monetary policy. The first is that movements in the target rate exhibit both the independent effects of monetary policy and shifts in demand for risk-free assets because the Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect the Fed's future actions because Fed officials could signal upcoming rate changes. Thus, when the Fed officially changes the target Federal funds rate, other rates may have already moved in expectation, which may appear as if Fed policy had no effect.

To obtain a measure of shocks, we closely adhere to the methodology of Swanson (2021) by considering the change in the policy indicator in a 1-day window around scheduled FOMC announcements. The policy indicators we employ are the first three principal components of the unanticipated change over the 1-day windows from January 2000 to March 2019 in the following five interest rates: changes in Federal funds rates futures for the current month, changes in Federal funds rates futures for the month of the next FOMC meeting, eurodollars

Table A8: Refinance During Tight Monetary Policy

	(1)	(2)	(3)
	July 2004 – June 2006	Dec 2015 – Dec 2018	combined
gap	0.907***	0.406***	0.484***
	(0.040)	(0.017)	(0.017)
CS	-0.294***	-0.071***	-0.131***
	(0.015)	(0.005)	(0.010)
gap × CS	0.006	0.080***	0.083***
	(0.013)	(0.004)	(0.006)
LTV	0.205***	-0.130***	-0.048
	(0.024)	(0.012)	(0.014)
DTI	0.098***	0.035***	0.062***
	(0.005)	(0.003)	(0.004)
rem. balance	0.141***	0.106***	0.105***
	(0.025)	(0.012)	(0.011)
# of borrowers	-0.002	0.014	0.014
	(0.009)	(0.005)	(0.005)
age	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
age × age	-0.002***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
age × age × age	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
constant	2.672***	2.149***	2.113***
	(0.116)	(0.105)	(0.069)
Age controls	X	X	X
Underwriting characteristics	X	X	X
Origination year-month FE	X	X	X
ZIP FE	X	X	X
Year-month × ZIP FE	X	X	X
Observations	9,990,268	27,826,298	37,816,566
R^2	0.007	0.004	0.005

Standard errors in parentheses
* $p < .00016$, ** $p < .00008$, *** $p < .000016$

Notes: The table reports LPM estimates of loan-level regression (A1) – the likelihood of mortgage refinance on a set of mortgage characteristics during tightening cycles of monetary policy.

futures contracts at horizons of 2, 3, and 4 quarters, and 2-, 5-, and 10-year Treasury yields.

We get the unanticipated changes in eight interest rates around FOMC meetings in two steps. First, we convert prices of all five futures to expected yields, in percentage points, by calculating $y_t = 100 - x_t$, where x_t is the quoted price on the contract and y_t is the implied yield to maturity. Second, we difference all variables across a window around FOMC announcements.

We scale changes in the Fed funds futures to take into account FOMC announcement timing. Before an FOMC meeting, the anticipated yield at settlement for the Fed Funds contracts expiring in the current month ($ff1_{t-\Delta t}$) is a weighted average of the average Fed Funds rate prior to the announcement (r_0) and the rate that is expected to hold for the remainder of the month (r_1):

$$ff1_{t-\Delta t} = \frac{d1}{D1} r_0 + \frac{D1 - d1}{D1} E_{t-\Delta t}(r_1) + \rho 1_{t-\Delta t}$$

where $d1$ is the day of the FOMC meeting, $D1$ is the number of days in the month and $\rho 1$ denotes risk premium. The surprise component is the change in the federal funds rate target given by

$$mp1_t = \left(ff1_t - ff1_{t-\Delta t}\right) \frac{D1}{D1 - d1}$$

As the window is small, we assume that the change in risk premium is zero. The same procedure is then applied to changes in the fed funds target after the second FOMC meeting from now (r_2). $ff2$ is the fed funds futures rate for the month containing the next FOMC meeting:

$$ff2_{t-\Delta t} = \frac{d2}{D2} E_{t-\Delta t}(r_1) + \frac{D2 - d2}{D2} E_{t-\Delta t}(r_2) + \rho 2_{t-\Delta t}$$

where $d2$ is the day of the next FOMC meeting, $D2$ is the number of days in the month of that meeting and $\rho 2$ denotes risk premium. Change in expectations for the second meeting is then given by

$$mp2_t = \left[\left(ff2_t - ff2_{t-\Delta t} \right) - \frac{d2}{D2} mp1_t \right] \frac{D2}{D2 - d2}$$

We collect these eight asset price responses into $T \times n$[25] matrix X, with rows corresponding to FOMC announcements and columns to different assets. We normalize each column of X to have zero mean and unit variance. As in Swanson (2021) and GSS (2005), we present these data in terms of a factor model,

$$X = F\Lambda + v \tag{A2}$$

where F is a $T \times 3$ matrix containing 3 unobserved factors, Λ is a 3×8 matrix of loadings of asset price responses on 3 factors, and v is a $T \times 8$ matrix of white noise residuals uncorrelated over time and across assets.

To estimate the unobserved factors F, we extract the first three principal components of X and rotate them to interpret as (i) the surprise component of the change in the federal funds rate at each FOMC meeting, (ii) the surprise component of the change in forward guidance, and (iii) the surprise component of any LSAP announcements. We impose the following identifying assumptions on the orthonormal rotation matrix. First, changes in forward guidance have no effect on the current federal funds rate. Second, changes in LSAPs have no effect on the current federal funds rate. Third, the variance of the LSAP factor is minimized in the pre-ZLB period corresponding to the sample from January 1, 1999, to February 1, 2009.

We perform two normalizations of the rotated factors. First, the sign of the first rotated column is such that it has a positive effect on the current federal funds rate, the second factor has a positive effect on the four-quarter-ahead Eurodollar future contract ED4, and the third factor has a negative effect on the 10-year Treasury yield. This way, an increase in the first two factors corresponds to a monetary tightening, whereas an increase in the third factor corresponds to an easing.[26]

[25] $T = 171$ because there are 171 FOMC meetings from January 1, 1999, to July 1, 2019. $n = 8$ because we use eight asset price changes.

[26] The goal was to leave the interpretation of the third factor as a purchase (LSAP) rather than

Table A9: Structural Loading Matrix

	$mp1$	$mp2$	$ed2$	$ed3$	$ed4$	2Y Tr.	5Y Tr.	10Y Tr.
Fed Funds	11.20***	8.10***	6.65***	6.23***	4.81***	0.04***	0.02***	0.01**
Rate	(0.24)	(0.18)	(0.38)	(0.15)	(0.32)	(0.00)	(0.00)	(0.00)
Forward	0.00	0.06	6.48***	8.02***	9.17***	0.06***	0.08***	0.06***
Guidance	(0.18)	(0.13)	(0.27)	(0.11)	(0.23)	(0.00)	(0.00)	(0.00)
LSAP	0.00	0.21	4.64***	4.45***	3.93***	-0.02***	-0.03***	-0.03***
	(0.16)	(0.12)	(0.25)	(0.10)	(0.21)	(0.00)	(0.00)	(0.00)
N	171	171	171	171	171	171	171	171
R^2_{adj}	0.93	0.92	0.88	0.98	0.93	0.89	0.99	0.92

Standard errors in parentheses
$^{*} p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$

Notes: Coefficients in the table correspond to elements of the structural loading matrix, in basis points per standard deviation change in the monetary policy instrument. $mp1$ and $mp2$ denote the scaled changes in the first and the third federal funds futures contracts, $ed2$, $ed3$, and $ed4$ denote changes in the second through fourth Eurodollar futures contracts; and 2Y, 5Y, and 10Y Tr. denote changes in 2-, 5-, and 10-year Treasury yields.

Second, we normalize each rotated factor to have a unit standard deviation, so the coefficients in all the regressions are in units of basis points per standard deviation change in the monetary policy instrument.

Table A9 reports the loading matrix implied by the identifying restrictions on the rotation matrix. Our results are broadly consistent with Swanson (2021) in signs and magnitude of coefficients, although we use daily rate data and employ a shorter sample to identify monetary policy shocks.

A one-standard-deviation increase in the federal funds rate factor is estimated to raise the current federal funds rate by 11.2 basis points, the expected federal funds rate at the next FOMC meeting by about 8 basis points, the second, third, and fourth Eurodollar futures rates by 6.7, 6.2, and 4.8 basis points respectively, and the 2-, 5-, and 10-year Treasury yields by about 0.04, 0.02, and 0.01 basis points respectively. We can see that the effects of a surprise change in the federal funds rate are largest at the short end of the yield curve and die off monotonically as the maturity of the interest rate increases.

The effect of forward guidance has a hump-shaped response, which peaks at

the sale of assets.

approximately the one-year horizon and then diminishes at longer horizons.[27] A one standard deviation increase in LSAP causes the 2-, 5- and 10-year treasury yields to fall on average.

We conclude that our high-frequency measure of monetary policy shocks corresponds pretty to changes in the federal funds rate, forward guidance, and LSAPs.

A12 First Stage for the IV Regression

We provide evidence that both shocks are plausible instruments for the mortgage rate gap. Table A10 provides first-stage regression estimates for each instrument, with panel A corresponding to the first measure of monetary policy shock and panel B corresponding to the second one. In both cases, we reject the null hypothesis of underidentification based on the Kleibergen-Paap rank LM statistic for robust errors. We also reject the null of weak instruments based on the Kleibergen-Paap Wald rank F statistic.

Coefficients in panel A of Table A10 are in basis points (bps) per standard deviation change in the policy instrument. The standard deviation of the fed funds rate factor is 8.39 bps, and forward guidance is 5.68 bps. That of LSAP is around $215 billion (which corresponds to a roughly 15 bp decline in the 10-year Treasury yield). Therefore, to compute the effects of a one-percentage-point change in the current federal funds rate target, we multiply the coefficient by 100bp/8.39bp ≈11.92. To compute the effects of a one-percentage-point change in the expected federal funds rate one year ahead, we multiply the coefficient by 100bp/5.68bp ≈17.61.

Point estimates in panel A of Table A10 suggest that forward guidance and LSAP factors affect the mortgage rate more than the federal funds rate. A one-percentage-point increase in the current federal funds rate target leads to a 19 bp decrease in the rate gap. A one-percentage-point increase in the expected federal funds rate one year ahead leads to an 85 bp decrease in the rate gap. Finally, a $215 billion surprise LSAP announcement leads to a 2.66 bp increase in the rate

[27] The forward guidance effect on the current federal funds rate is zero by construction.

gap.

Point estimates in panel B of Table A10 imply that a one-percentage-point monetary policy shock increases the rate gap by 56 bps. Overall, estimates for both instruments are consistent with those from Eichenbaum et al. (2022) and Gertler and Karadi (2015).

A13 Household Problem Solution

Households' consumption-savings decision and the evolution of the joint distribution g_t over state vector can be characterized with two differential equations: Hamilton-Jacobi-Bellman variational inequality (HJBVI) and Kolmogorov Forward equation (KFE). HJBVI is given by

$$\begin{aligned}\min\{&\delta V - U(C^{\text{pay}}) - \partial_W V S^{\text{pay}} - \mathscr{L} V - \mathscr{L}_{CS}^{\text{pay}} V, \\ &\delta V - U(C^{\text{nopay}}) - \partial_W V S^{\text{nopay}} - \mathscr{L} V - \mathscr{L}_{CS}^{\text{nopay}} V\} = 0\end{aligned} \tag{A3}$$

where $U(C)$ is the instantaneous value of consumption, $\partial_W V S^{\text{pay}}$ is the change in value because of additional savings, $\mathscr{L}$ is the infinitesimal operator associated with the changes in income, market rate, and refinancing, $\mathscr{L}_{CS}$ is the infinitesimal operator associated with the changes in credit score. We solve our HJBVI using a standard finite difference scheme with upwinding.

Note that optimal consumption satisfies a usual first-order condition: the marginal utility of consumption is equal to the marginal value of wealth. Finally, there is a state constraint $W_t \geq \underline{w}$. The first order condition $u'(V(\underline{w}, r, m^*, Y)) = \partial_W V(\underline{w}, r, m^*, Y)$ still holds at the borrowing constraint. To respect the constraint, one needs $\mu_W(\underline{w}, r, m^*, Y) = r\underline{w} + Y - C(W, r, m^*, Y) - m^* F \geq 0$. Combining with the FOC, the state constraint motivates a boundary condition

$$\partial_W V(\underline{w}, r, m^*, Y) \geq u'(V(\underline{w}, r, m^*, Y)) \tag{A4}$$

A13.1 HJB Equation

To solve a non-linear partial differential equation (PDE) for V, we use a finite difference method following Achdou, Buera, Lasry, Lions and Moll (2014). We

Table A10: First Stage Estimates

Panel A. 3-factor Monetary Policy Shock		
Dependent variable	gap	gap× CS
	(1)	(2)
Fed Funds Rate (bps per st.dev.)	-1.568*	0.469
	(0.361)	(0.334)
Forward Guidance (bps per st.dev.)	-4.786***	0.035
	(0.569)	(0.182)
LSAP (bps per st.dev.)	2.660***	0.250
	(0.402)	(0.271)
F_{st}	100.75	43.54
Underidentification test		
Kleibergen-Paap rk LM_{st}	37.59	
Weak identification test		
Kleibergen-Paap Wald rk F_{st}	62.21	
Observations	79,762,158	79,762,158

Panel B. Monetary Policy Shock based on 2-year Treasury Yield		
Dependent variable	gap	gap× CS
	(1)	(2)
Δ 2-year Treasury Yield (ppts)	-0.561***	-0.062***
	(0.025)	(0.011)
F_{st}	251.74	48.78
Underidentification test		
Kleibergen-Paap rk LM_{st}	23.14	
Weak identification test		
Kleibergen-Paap Wald rk F_{st}	43.77	
Observations	79,762,158	79,762,158

Standard errors in parentheses
* $p < .00011$, ** $p < .000056$, *** $p < .000011$

Notes: The table reports the first stage from the instrumental variable estimation of loan-level regression (A1). In Panel A, instruments for the rate gap are 3-factors from PCA of eight interest rate changes around FOMC announcement days, and instruments for gap×CS are corresponding interactions of 3 factors with credit score. Coefficients are in basis points per standard deviation change in the policy instrument. In Panel B, the instrument for the gap is the change in 2-year Treasury yield around the FOMC announcement, and the instrument for gap×CS is the corresponding interaction of shock with credit score. Coefficients are in percentage points. The estimation is performed on the monthly frequency using a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-month. All specifications include age controls, a full set of underwriting characteristics, and a full set of origination year-quarter-by-ZIP-code fixed effects. Standard errors are double clustered by 3-digit ZIP code and origination year-quarter.

denote $V_{k,i,m,j}$ the value function in aggregate state i (with r_i) for a household in idiosyncratic state j (with Y_j), with wealth W_k, and outstanding mortgage rate m^*_m. We approximate function $V_{k,i,m,j}$ at n_w discrete points in the space dimension, w_k, $k = 1, ..., n_w$. We use equispaced grids, denoting by Δ_w the distance between grid points of vector W. The derivative $\partial_W V(W_k, r_i, m^*_m, Y_j) = \partial_W V_{k,i,m,j}$ is approximated with either a forward or a backward difference approximation

$$\begin{aligned} \partial_W V_{k,i,m,j} &\approx \frac{V_{k+1,i,m,j} - V_{k,i,m,j}}{\Delta_w} \equiv \partial_W V_{k,i,m,j,F} \\ \partial_W V_{k,i,m,j} &\approx \frac{V_{k,i,m,j} - V_{k-1,i,m,j}}{\Delta_w} \equiv \partial_W V_{k,i,m,j,B} \end{aligned} \tag{A5}$$

We use the upwind scheme to determine which approximation to use. When the drift of the state variable, savings μ_W, is positive, we use a forward difference. When the drift is negative, we use a backward difference:

$$\begin{aligned} \partial_W V_{k,i,m,j} = \partial_W V_{k,i,m,j,F} \mathbb{1}\{\mu_{k,i,m,j,F} > 0\} + \partial_W V_{k,i,m,j,B} \mathbb{1}\{\mu_{k,i,m,j,B} < 0\} \\ + \partial_W \bar{V}_{k,i,m,j} \mathbb{1}\{\mu_{k,i,m,j,F} \leq 0 \leq \mu_{k,i,m,j,B}\} \end{aligned} \tag{A6}$$

where $\partial_W \bar{V}_{k,i,m,j} = u'(Y_j + r_i W_k - M^*_m F)$. Similarly, we use an upwind method in the r- and $Y-$ directions. For the second-order derivative, we use a central difference approximation.

The boundary condition (A4) is enforced by setting

$$\partial_W V_{1,i,m,j,B} = u'(V(b_{CS}, r, m^*, Y)) \tag{A7}$$

The finite difference approximation to (A3) is

$$\frac{V^{n+1}_{k,i,m,j}-V^{n}_{k,i,m,j}}{\Delta_t}+\delta V^{n+1}_{k,i,m,j}=u(C^{n}_{k,i,m,j})+(\nu+\chi_{CS}\mathbb{1}\{m(r)<m^*\})\left(V^{n+1}_{k,i,i,j}-V^{n+1}_{k,i,m,j}\right)$$
$$+\partial_W V^{n+1}_{k,i,m,j,F}\left[\mu^{n}_{k,i,m,j,F}\right]^{+}+\partial_W V^{n+1}_{k,i,m,j,B}\left[\mu^{n}_{k,i,m,j,B}\right]^{-}$$
$$+\partial_r V^{n+1}_{k,i,m,j,F}\left[\mu(r_k)\right]^{+}+\partial_r V^{n+1}_{k,i,m,j,B}\left[\mu(r_k)\right]^{-}+\partial^2_{rr}V^{n+1}_{k,i,m,j}\frac{\sigma^2(r_k)}{2}$$
$$+\partial_Y V^{n+1}_{k,i,m,j,F}\left[\mu(Y_j)\right]^{+}+\partial_Y V^{n+1}_{k,i,m,j,B}\left[\mu(Y_j)\right]^{-}+\partial^2_{YY}V^{n+1}_{k,i,m,j}\frac{\sigma^2(Y_j)}{2} \tag{A8}$$

where Δ_t is the step size, and for any number x, $x^+=\max\{x,0\}$ and $x^-=\min\{x,0\}$.

Equation (A8) constitutes a system of $n_w\times n_r\times n_{m^*}\times n_Y$ equations, and can be written in matrix notation

$$\frac{1}{\Delta_t}(V^{n+1}-V^n)+\delta V^{n+1}=u^n+A^nV^{n+1} \tag{A9}$$

where u^n is a vector with elements $\{u(C^n_{k,i,m,j})\}$, A^n is the intensity matrix that encodes the evolution of the stochastic process of all state variables, and V^{n+1} is the unknown value vector. A^n satisfies all the properties of a Poisson transition matrix: all rows sum to zero, diagonal elements are non-positive, and off-diagonal elements are non-negative.

A13.2 KFE Equation

To compute impulse response functions, I approximate the density at $n_w\times n_r\times n_Y$ discrete points. Given initial condition g^0, the KFE is iteratively solved by solving the following system:

$$\frac{g^{n+1}-g^n}{\Delta_t}=(A^n)^Tg^{n+1} \tag{A10}$$

where $(A^n)^T$ is the transpose of the intensity matrix A^n.

A14 Model Parameter Values

Table A11: Model Exogeneous Parameter Values

Parameter	Value	Description	Target or Source
Income			
$\ln 2/\eta_Y$	7.35 years	half-life of (log) income shock	Floden and Lindé (2001)
σ_Y	21% p.a.	(log) income volatility	Floden and Lindé (2001)
$E[Y_t]$	$69,560	(unconditional) income mean	US household average in 2019
Interest Rate			
$\ln 2/\eta_r$	2.48 years	half-life of interest rate shock	3-month Treasury yields
σ	7.0% p.a.	interest rate volatility	3-month Treasury yields
$\bar{r}$	4.1% p.a.	(unconditional) interest rate mean	mean mortgage rate 3.7% in 2019Q4
Mortgage Rate			
α_0	2.33%	constant term of mortgage rate function	regression of mortgage rate on 3-month Treasury yields
α_1	0.43%	slope of mortgage rate function	regression of mortgage rate on 3-month Treasury yields
Other Structural Parameters			
γ	2	risk aversion	literature
δ	10% p.a.	household discount rate	mean wealth of $75,200
			weighted average of wealth (excluding home equity)
			for Generation X and Baby Boomers
F	$225,000	mortgage balance	average in data

Notes: The table presents the model's calibrated parameters. See text for details.

Table A12: Refinance and Borrowing Parameters' Values

Parameter	Value	Description	Target or Source
ν	8.4% p.a	arrival rate of moving shock	refinance rate for $gap < 0$ in data
χ	27% p.a	arrival rate of refinance shock	refinance rate for $gap > 0$ in data
χ_L	0% p.a	shock arrival rate for the low credit score group	assumption
χ_M	26% p.a	shock arrival rate for medium credit score group	refinance rate for $gap > 0$, FICO < 75^{th} percentile
χ_H	50% p.a	shock arrival rate for high credit score group	χ in the homogeneous economy, given χ_L, χ_M
λ	60%	default probability if miss payment	average
Credit Score			
$\ln 2/\eta_{CS}$	7.84 years	half-life of credit score repair	credit score distribution in data
σ_{CS}	50	credit score volatility	standard deviation of credit score in data
$E[CS_t]$	750	(unconditional) credit score mean	mean of credit score in data
Spread between short-term borrowing and saving rates			
r^L	12%	spread for low credit score group	credit score distribution in data
r^M, r^H	0%	spread for medium and high credit score groups	

Notes: The table presents the model's calibrated parameters. See text for details.

A15 Calibration of Parameters for Short Term Interest Rate Process

We follow Cox et al. (1985) to estimate parameters of (5) using the generalized method of moments (GMM). We start with Euler discretization to obtain

$$\begin{aligned} r_{t+1} &= \alpha + \beta r_t + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= \sigma \sqrt{r_t} \sqrt{\Delta t} N(0,1) \end{aligned} \tag{A11}$$

where $\beta = -\kappa \Delta t$, $\alpha = \kappa \mu \Delta t$, and $N(0,1)$ is a random shock with zero mean and unit variance. From (A11) it follows that

$$\begin{aligned} E[\varepsilon_{t+1}] &= 0 \\ E[\varepsilon_{t+1}^2] &= \sigma^2 r_t \end{aligned} \tag{A12}$$

Using (A12) and orthogonality condition, one derives moment conditions $E[g(\kappa,\mu,\sigma)] = 0$, where

$$g(\kappa,\mu,\sigma) = \begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_{t+1} r_t \\ \varepsilon_{t+1}^2 - \sigma^2 r_t \\ (\varepsilon_{t+1}^2 - \sigma^2 r_t) r_t \end{bmatrix}$$

The corresponding sample moments are given by

$$\hat{g}(\kappa,\mu,\sigma) = \frac{1}{T} \sum_{t=1}^{T} g(\kappa,\mu,\sigma)$$

where T is the number of observations. The GMM moment function is defined as

$$J = \hat{g}'(\kappa,\mu,\sigma) \hat{W} \hat{g}(\kappa,\mu,\sigma)$$

where $\hat{W}$ is weighting matrix. The parameter estimates are found by minimizing J with respect to κ, μ, σ.

This model is overidentified – there are four-moment conditions and three parameters to estimate. We estimate GMM in two stages. First, we minimize the objective function using the identity weighting matrix. We use estimates from the first stage to get $\hat{W} = \hat{S}^{-1}$, where $\hat{S}$ is an estimate of the spectral density matrix of population moment functions. We use the Newey-West estimator of the spectral density matrix

$$\hat{S} = \hat{S}_0 + \sum_{j=1}^{k} \left(1 - \frac{j}{k+1}\right)\left(\hat{S}_j + \hat{S}'_j\right)$$

where

$$\hat{S}_j = \frac{1}{T} \sum_{t=j+1}^{T} g_t(\kappa, \mu, \sigma) g'_{t-j}(\kappa, \mu, \sigma)$$

This choice of weighting matrix results in asymptotically efficient estimates.

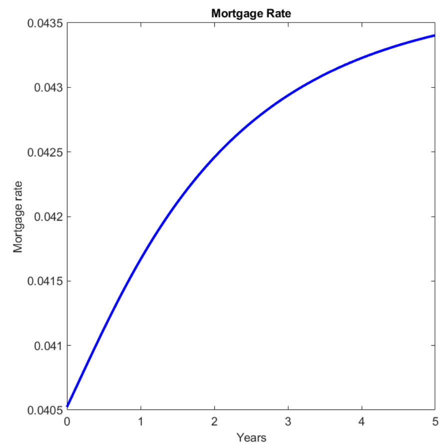
For the estimation, we use daily data for 3-month Treasury yields from 1992 to 2019. This yields $T = 4003$ observations. We set $dt = 1/250$ and the number of lags in spectral density decomposition $k = 12$.

A16 Monetary Policy in the Ergodic Economy

In this subsection, we study the impact of expansionary monetary policy on average coupons, refinancing, and consumption in economies with and without credit score heterogeneity. Our main experiment compares impulse response functions (IRFs) of the homogeneous economy and the heterogeneous economy under the economy's ergodic density. We set an initial interest rate equal to $\bar{r}$. We look at the IRFs to a one-percentage-point (100bps) cut in initial interest rate, which causes mortgage rates to decrease by 0.43 percentage points (43bps) on impact, depicted in Figure A4.

Figure A5 compares the IRFs of average coupons (left panel), aggregate refinance (middle panel), and aggregate consumption (right panel) in the homogeneous economy (orange) and the heterogeneous economy starting from ergodic steady state. The average coupon of outstanding mortgages responds to monetary policy more strongly in the homogeneous economy. This difference is due to the self-selection of households with lower credit scores into the higher interest rate gaps in the steady state we discussed in the previous section. While all the consumers can refinance in the homogeneous economy, in the heterogeneous

Figure A4: IRF of Mortgage Rate to 100 bps Decline in r



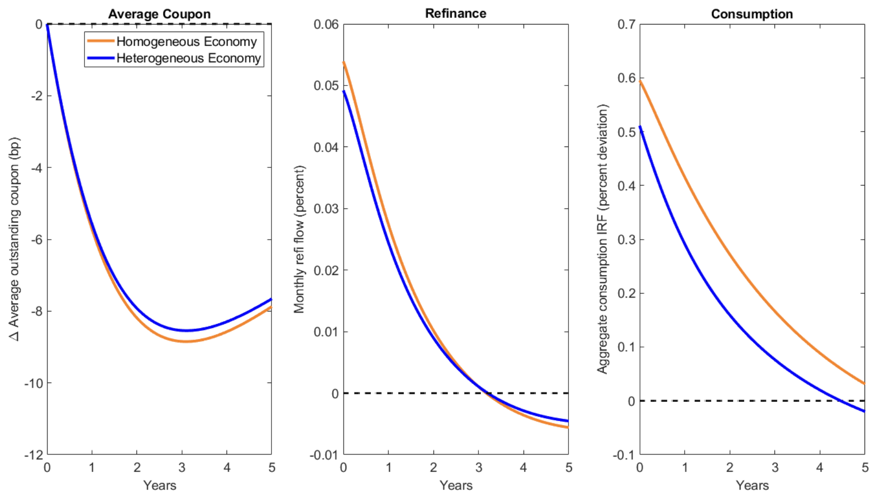
economy, households with low credit scores remain locked in high rates, although they would have benefited from refinancing the most.

The middle and right panels of Figure A5 show how average coupon differences translate into differences in refinancing and consumption. Average refinancing rates in the homogeneous economy and the heterogeneous economy are calibrated to be the same. However, refinance responses are smaller in the economy with credit score heterogeneity due to the differences in the initial coupon distribution discussed above.

There are substantial differences between aggregate consumption responses in the homogeneous economy and the heterogeneous one. The increase in consumption is approximately 14% lower on impact in the heterogeneous economy and 41% lower after two years.

In our setup, monetary policy affects household consumption through two channels, which we refer to as the Euler channel and the refinancing channel. The Euler channel is the standard liquid wealth effect: the cut in interest rate decreases the return on wealth for all agents and makes short-term borrowing cheaper. The refinancing channel stems from the fact the interest rate cut provides higher credit score households with the refinancing option. That allows them to reset their mortgage rate to a lower one and free up disposable income for additional consumption.

Figure A5: IRFs to 100 bps Decline in r starting from Ergodic Distribution

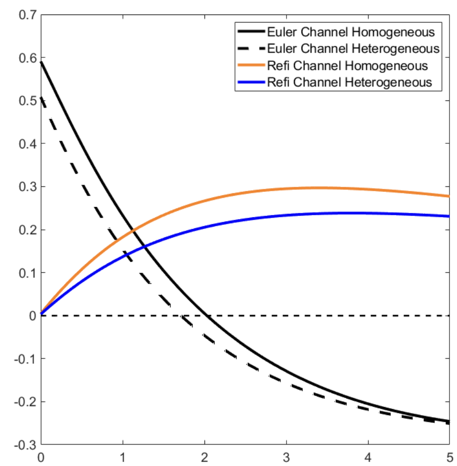


Notes: The figure shows the IRFs of average coupon (left panel), aggregate refinance (middle panel), and aggregate consumption (right panel) for the homogeneous economy (orange) and the heterogeneous economy (blue), starting from the ergodic distribution.

To disentangle Euler and refinancing channels of spending from each other, we proceed as follows. First, we solve the homogeneous model with refinancing to generate the initial distribution of household states. Second, we solve for a new policy function in which the transition matrix for refinancing is set to zero. The refinancing channel is then the difference between solutions in steps one and two. Finally, we repeat the same steps for the heterogeneous model.

In Figure A6, we decompose the consumption response into these two channels. Solid black and dashed black lines show the impact of the Euler channel in the homogeneous economy and the heterogeneous one. Colored lines demonstrate the effects of the refinancing channel in the homogeneous economy and the heterogeneous economy. The effects of the refinance channel remain 20-30% lower in the heterogeneous economy over five years.

Figure A6: Consumption Response Decomposition



Notes: The figure decomposes the IRF of aggregate consumption into Euler (solid black and dashed lines) and refinancing (orange and blue) channels in the homogeneous economy and the heterogeneous economy, starting from the ergodic distribution. See the text for details.

The effects of the two channels have very different time profiles. The impact of the Euler channel comes "on-impact" right at the time of the shock but is short-lived, hitting zero after two years and reversing later due to a negative impact on wealth. On the other hand, the effect of the refinancing channel does not arrive instantly; instead, it is longer lasting and does not wear off even after five years. Even though the refinancing activity increases on impact (see the middle panel of Figure A5), it takes more time for the significant benefits to arrive, as smaller monthly payments lead to the accumulation of wealth.

The response from the refinancing channel is lower in the heterogeneous economy due to two main effects. First, there are low credit score households that are cut off from refinancing opportunities and cannot claim the benefits of lower mortgage rates. Second, the presence of credit score heterogeneity leads to a higher precautionary motive and brings down the MPCs out of mortgage rates. Intuitively, the relative importance of the no-refinancing and MPC effects depends on the initial distribution of coupon rates. If coupon rate distributions of high and low credit score groups are closer to each other, the MPC effect accounts for a larger share of the response from the refinancing channel. If these coupon rate distributions are further apart, the no-refinancing effect becomes stronger.

Figures 6 and 7 in the main text show that the differences between the homogeneous economy and the heterogeneous one are magnified if we start from the actual distribution of coupon rates by credit score groups from 2019 rather than the ergodic one. The aggregate consumption response in the heterogeneous economy is 23% lower on impact and 51% lower after two years. The no-refinance effect in this economy is stronger than in the ergodic economy, while the MPC effect is weaker. The peak consumption response through the refinancing channel occurs three years after the shock and is equal to 35 bps in the homogeneous economy. At the same time, it is only 26 bps in the heterogeneous economy resulting in a 33 % difference. It is so because the 2019 coupon distribution features many pre-crisis loans with high rates and low credit scores.

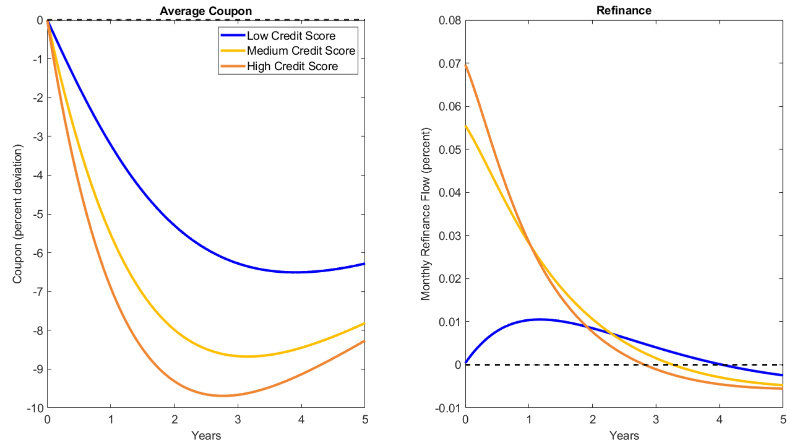
A17 Monetary Policy Disparities in the Ergodic Economy

We start our redistribution analysis in Figure A7, where we decompose the IRFs of average coupon and refinance from Figure A5 by credit score group. Note that the low credit score group cannot refinance by construction. However, IRFs for average coupon and refinance are not zero because, conditional on keeping up with mortgage payments, households can move to higher credit score groups.

To explore how this heterogeneity in refinancing opportunities affects households, in Figure A8, we provide the refinancing channel portion of wealth (left panel) and consumption (right panel) responses. The wealth of all the credit score groups increases due to mortgage refinancing. However, the low credit score group experiences a much lower rise in their wealth than other groups. They cannot refinance their mortgage and end up paying higher coupons every month. This effect accumulates over time, contributing to wealth inequality. At its peak, which occurs 14 years after the shock, the increase in the wealth of the low credit score group is 23%. For the high credit score group, after 14 years, this number is 38%, which is twice as large.

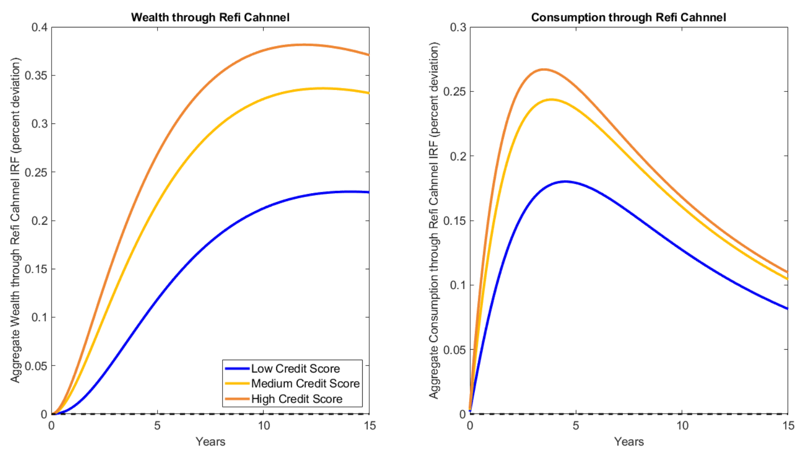
Heterogeneity in refinancing contributes to consumption inequality as well.

Figure A7: IRFs to 100 bps Decline in r by Credit Score Group



Notes: The figure shows the IRFs of average coupon (left panel) and aggregate refinance (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. See the text for details.

Figure A8: Refinancing Channel of 100 bps Decline in r by Credit Score Group



Notes: The figure shows the refinancing channel portion of the IRFs of aggregate wealth (left panel) and aggregate consumption (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. See the text for details.

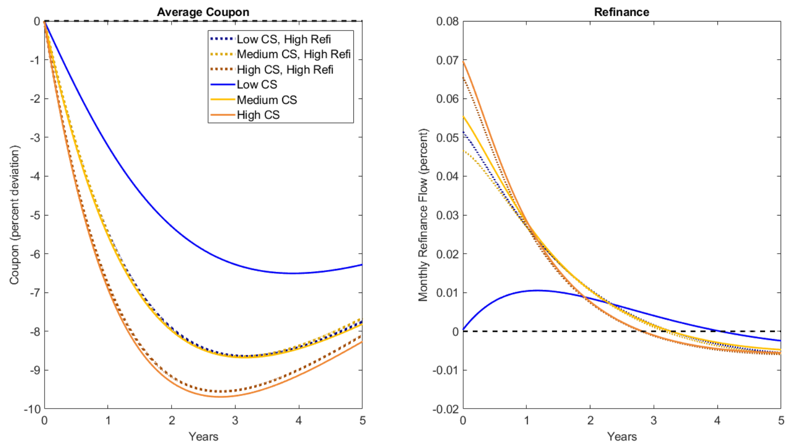
The peak response of the low credit score group's consumption is 18%, occurring 4.5 years after the shock. For the high credit score group, the corresponding number is 26%, resulting in a 36% difference between the groups.

To smooth out these disparities in wealth and consumption, one would need a policy that addresses heterogeneity in refinancing while keeping delinquency rates low. To discuss the consequences of such a policy, we consider monetary transmission a counterfactual economy that preserves heterogeneity with respect to credit scores but allows the low credit score group to refinance at the same rate as the medium one.

In Figure A9, we provide IRFs for the heterogeneous model we employed before along with those for the economy where $\chi_L = \chi_M$. Average coupons and refinance of the low credit score group are now very close to those of the medium one. They are not exactly the same because different groups still face different costs of short-term borrowing.

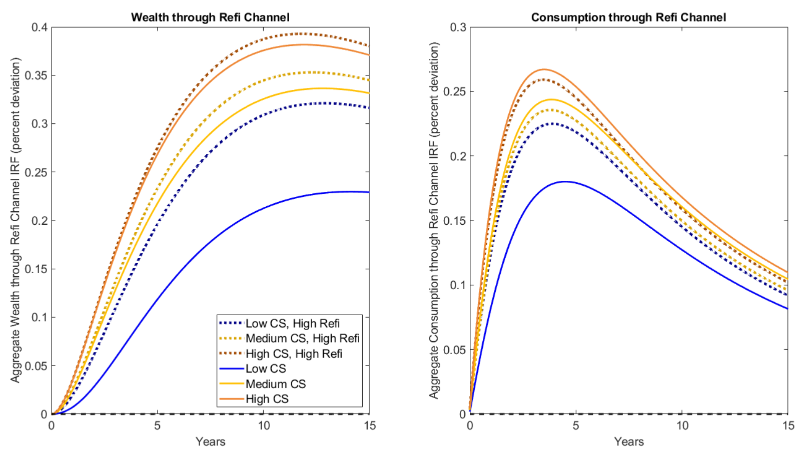
In the economy where low credit score group refinances at a higher rate, the wealth response disparities significantly shrink, as shown in Figure A10. At the same time, contrary to the concern, debt delinquency rates slightly decrease, both on the aggregate and for the lower credit score group in particular. The latter effect is caused by the increasing refinancing opportunities that allow consumers to take advantage of lower rates, decrease their mortgage costs, and make it less attractive to skip payments.

Figure A9: IRFs to 100 bps Decline in r by Credit Score Group



Notes: The figure shows the IRFs of average coupon (left panel) and aggregate refinance (right panel) by low (blue), medium (yellow), and high (orange) credit score groups for the baseline heterogeneous economy (solid lines) and counterfactual economy (dashed line). See the text for details.

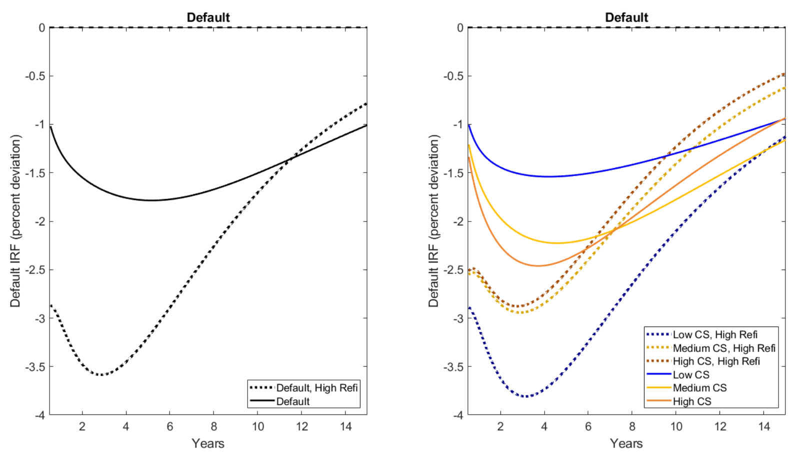
Figure A10: Refinancing Channel of 100 bps Decline in r by Credit Score Group



Notes: The figure shows the refinancing channel portion of the IRFs of aggregate wealth (left panel) and aggregate consumption (right panel) by low (blue), medium (yellow), and high (orange) credit score groups. See the text for details.

A18 Delinquency Rate Response to Rate Cut

Figure A11: Delinquency IRFs to 100 bps Decline in r



Notes: The figure shows the delinquency rate IRFs for the aggregate economy (left panel) and each credit score group (right panel) for the baseline heterogeneous economy (solid lines) and the counterfactual economy (dashed line). The initial distribution corresponds to the 2019 distribution. See the text for details.