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 Loan-Level historical data, we show that a 1% increase in mortgage rate increases the refinancing probability for borrowers with a FICO credit score of 800 twice as much as that of borrowers with a FICO score of 700. We then develop a refinancing model and find that credit score heterogeneity dampens consumption response to monetary policy by 11%, compared to a standard model with only mortgage rate heterogeneity. Borrowers with lower credit scores face tighter borrowing limits and benefit from refinancing more than borrowers with higher credit scores, but face more difficulties obtaining refinance loans, resulting in a smaller consumption response.

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1 Introduction

Monetary policy can stimulate household consumption and wealth by lowering mortgage costs through refinancing. Fixed-rate mortgages (FRMs) are the most significant source of household debt and, therefore, one of the primary mechanisms for monetary policy transmission.[1] Lower interest rates lead FRM holders with rates higher than the current market rate (i.e. positive rate gaps) to refinance.[2] The consequent decline in mortgage debt payments generates an increase in wealth and consumption.

The extent of monetary policy transmission to FRM refinancing depends not only on the number of mortgages with positive rate gaps, but also on households' willingness and ability to refinance their mortgages. On the one hand, many borrowers refinance sub-optimally; this heterogeneity in refinancing is associated with inattention and demographic characteristics. [3] On the other hand, refinance loans are subject to rigorous underwriting criteria that represent a credit constraint to some borrowers and potentially depend on the state of the economy.[4] The existence of credit constraints related to underwriting criteria (credit score, for instance) can lead to heterogeneous monetary policy effects because not all borrowers with positive rate gaps are able to access mortgage markets. This heterogeneity in refinancing opportunities can therefore dampen the effects of monetary policy.

In this paper, we combine empirical patterns from monthly loan-level data and a heterogeneous agent model of mortgage refinancing to show that monetary transmission through the FRM channel is limited because it depends on borrowers' credit score distribution in addition to their rate gap distribution. The intuition behind this mechanism is as follows: borrowers with lower credit scores have higher marginal propensities to consume (MPCs). They benefit from refinancing more than borrowers with higher credit

[1] Goodman, McCargo, Golding, Parrott, Pardo, Hill, Kaul, Bai, Strochak, Reyes, and Walsh (2019) document that in the U.S. mortgages make up 65% of all household liabilities and roughly 60% of them have a fixed-rate and maturity of 30 years.

[2] We refer to the difference between the outstanding mortgage rate on a loan and the current market rate on similar mortgages as a "rate gap."

[3] See Bhutta and Keys (2016), Johnson, Meier, and Toubia (2019), Agarwal, Ben-David, and Yao (2017), Andersen, Campbell, Nielsen, and Ramadorai (2020), Gerardi, Willen, and Zhang (2020).

[4] Over the last years, the fraction of denied refinance applications was higher than the fraction of denied purchase applications. According to HMDA data, in 2007 banks denied 30% of refinancing and 20% of purchase loan applications; in 2017 those numbers were 19% and 12% respectively. The main reasons for their denial include bad credit history, high debt-to-income ratio, and low collateral value (high loan-to-value ratio).

scores, but are less likely or able to refinance and borrow. Therefore, the associated change in aggregate consumption in response to monetary policy is lower compared to scenarios where people with the most extensive benefits from refinancing can freely refinance.

To deliver detailed results on credit score heterogeneity of refinance response to monetary policy and motivate a heterogeneous agent model of refinancing, we begin with a detailed empirical analysis using Fannie Mae Single-Family Loan-Level historical data. We estimate that a 1% decrease in mortgage rate increases the refinancing probability for borrowers with a FICO credit score of 800 twice as much as that of borrowers with a FICO score of 700. Our refinancing model suggests that this heterogeneity is economically significant – it dampens the aggregate consumption response to monetary policy by approximately a 11% compared to a standard model with only mortgage rate heterogeneity.

In the empirical part of the paper, we document credit score heterogeneity of the refinancing response to changes in mortgage rates in four steps. First, we motivate our study of borrowers' credit score heterogeneity by illustrating the connection between credit score distribution and refinancing. Second, we show that, for each rate gap, there are significant differences in the refinancing hazards of lower and upper quartile credit score borrowers. Third, we show that differences in refinancing between different credit score groups are explained by borrowers' differential sensitivities to changes in mortgage rates, even when controlling for observable loan characteristics and fine geographic-by-time fixed effects. Fourth, we exploit exogenous changes in monetary policy to measure the marginal effect of credit score heterogeneity on refinancing to avoid bias caused by omitted variables that affect both mortgage rate and refinancing through channels distinct from monetary policy.

To motivate our analysis of credit score heterogeneity, we start with the observation that borrowers with higher credit scores are the ones who refinance most actively, coupled with the confirmation of time-varying credit score distribution. A borrower's credit score is one of many underwriting criteria that affect refinancing opportunities and refinancing. Time-varying credit score distribution suggests that refinancing opportunities change over time. These findings suggest that credit scores are another potential source of refinancing heterogeneity besides rate gaps.

Our second step is to show that, for each rate gap, there are significant differences between the fraction of refinancing loans among borrowers in different credit score quartiles. We do so by characterizing the refinancing hazard as a non-parametric function of the rate gap and credit score bin. Pooling observations across time, we sort borrowers into rate gap and credit score quartiles and calculate the fraction of loans that refinance for each rate gap and in each 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 for loans with negative rate gaps, and are high and constant for loans with positive gaps. However, among mortgages with positive rate gaps, loans with credit scores in upper quartile have a much higher probability of refinancing than loans in the lower credit score quartile. The difference in refinancing between lower and higher credit score quartiles is robust to excluding loans with high LTV ratios, observations during 2007 – 2011 when households were more likely to be unemployed, and loans with substantial remaining balances.

The third step is to show that the large differences in refinancing probabilities between different credit score groups can be explained by their differential sensitivities to mortgage rates. To establish that the lower credit score borrowers are less likely or less able to refinance when rates decline, we regress refinancing on rate gap, credit score, and the interaction term between the two. The strong relationship between refinancing and the interaction of rate gap with credit score is robust to inclusion of rate gap interactions with other borrower characteristics, using alternative definitions of rate gaps, controlling for payment history, aggregation to quarterly frequency, and aggregation to a 3-digit ZIP-code level. This result is driven by the episodes of mortgage rate decreases and is much smaller during tightening cycles of monetary policy.

To quantify the effect of the credit score heterogeneity on refinancing, we instrument rate gaps with high-frequency monetary shocks to avoid endogeneity due to confounding factors such as households' liquidity constraints during recessions that prevent them from paying refinancing costs. A 1% increase in rate gap leads to a 1.25 percentage point increase in the likelihood of refinancing for borrowers with a credit score of 800, but only 0.54 percentage points for borrowers with a credit score of 700. This marginal impact of a standard deviation increase in credit score amounts to 27% of average monthly refinancing rate.

Since the data linking spending and refinancing is limited, we build a heterogeneous agent model with fixed-rate mortgages using Berger, Milbradt, Tourre, and Vavra (2021) baseline as a a benchmark, in order to show that credit score heterogeneity matters for monetary transmission to aggregate consumption. The model features a consumption-savings decision in an incomplete market setting, labor income risk, and refinancing of fixed-rate mortgages. Refinancing enters via a Calvo-style exogenous shock – households refinance at Poisson arrival times only if their rate gap is positive. The novel feature of our model is the means by which it integrates credit score heterogeneity: credit score determines household's ability to refinance and borrow through arrival rate of refinancing shock and borrowing limits on short-term debt. Intuitively, credit score is a prediction of how likely household is to pay a loan back. If this probability is low, households cannot refinance mortgage and borrow more unsecured debt.

The credit score heterogeneity dampens borrowers' consumption response to monetary policy by 11% on impact compared to the standard model with only rate gap heterogeneity. Consumers with low credit scores face tighter borrowing limits and have lower chances to refinance. They are also the ones who exhibit higher MPCs than households with higher credit scores, dampening the efficacy of monetary transmission.

Related Literature

Our paper contributes to contemporary mortgage research in three significant ways. First, we extend the existing literature on the mortgage market in monetary policy implementation by quantifying monetary policy transmission to the refinancing of FRMs using loan-level data. Second, we shed light on a novel source of heterogeneity of monetary policy transmission - credit score, which inhibits the smooth functioning of this channel. Finally, we identify refinancing heterogeneity by individuals with different credit scores, thus contributing to the newly emerging strand of literature that highlights the redistribution effects of monetary policy.

A vast empirical literature stressed the importance of the mortgage market as a principal channel through which monetary policy affects the economy. The first papers in this strand of literature evaluated monetary policy transmission to households through 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 the US housing (see Berger, Milbradt, Tourre, and Vavra (2021), DiMaggio, Kermani, and Palmer (2020), Beraja, Fuster, Hurst, and Vavra (2018), and Eichenbaum, Rebelo, and Wong (2022)). In this paper, we further extend the existing literature by estimating the effect of monetary policy on the refinancing of

30-year FRMs with loan-level panel data.

One branch of literature on the efficacy of monetary policy through the mortgage channel examines supply-side constraints. Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018) show that even though marginal probability to borrow is higher for the lowest FICO credit score consumers, higher credit limits resulting from credit expansion policies reduce profits from lending, leading to a decrease of aggregate borrowing. Greenwald (2018) emphasizes the importance of loan-to-value ratios and debt debt-to-income ratios. Beraja, Fuster, Hurst, and Vavra (2018) examine the effect of regional changes in house prices on the ability of households to refinance their mortgages. While we also study a supply-side heterogeneity of monetary policy transmission - credit score, we focus only on rate refinancing and ignore refinancing due to house price changes which are indirectly affected by monetary policy.

Another branch of this literature concentrates on demand-side factors affecting refinancing. Berger, Milbradt, Tourre, and Vavra (2021) and Eichenbaum, Rebelo, and Wong (2022) have shown that refinancing rate incentives vary over time because FRM allows a borrower to *choose* whether they want to be exposed to a particular rate. While these papers focus on the effects of time-varying mortgage rate incentives on monetary policy, 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. Credit score heterogeneity dampens monetary policy transmission to housing wealth compared to the case where people with the most extensive benefits from refinancing can freely do so.

Finally, our paper is the first one to identify refinancing heterogeneity by individuals with different credit scores, thus contributing to the newly emerging strand of literature that highlights the redistribution effects of monetary policy. 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).

Structure of the Paper. The structure of the paper is as follows. Section 2 describes Fannie Mae Single-Family Loan-Level data we use in our empirical analysis. Section 3 documents empirical results on credit score heterogeneity. In section 4, we use a refinancing model to show that credit score heterogeneity dampens housing wealth response to monetary policy. Section 5 concludes.

2 Data

To show that borrowers with lower credit scores are less likely to refinance in response to monetary policy we use Fannie Mae Single-Family 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 (Goodman, McCargo, Golding, Parrott, Pardo, Hill, Kaul, Bai, Strochak, Reyes, and Walsh (2019)). 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 acquired by Fannie Mae. Each loan is tracked at a monthly frequency from the month of origination until it is paid off voluntarily or involuntarily via the foreclosure process. 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 in the January 2000 – March 2019 period. The data on loan performance extends through June 2019. In order to focus on a homogeneous mortgage product, 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 our analysis is conducted 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 construct our sample by selecting a 10 percent random sample of loans originated in each quarter during our sample period.[6] We impose additional sample restrictions to address outliers and missing information on key observable variables. Appendix **??** lists all the restrictions in detail. The total number of FRMs is 3,580,928, resulting in 149,070,748 loan-month observations. In our analysis, we employ the remaining loan balance in each month from origination to prepayment and information on outstanding (fixed) interest rate, FICO credit score, debt-to-income ratio (DTI), loan-to-value ratio (LTV), loan purpose (cash-out refinance, rate refinance, purchase of a new house), MSA and a 3-digit ZIP-code recorded at the

[5] Available at `http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html`

[6] We experimented with selecting a 10 percent random sample of all loans from the dataset, but all the results were not statistically different.

time of mortgage origination.[7,8]

We treat mortgages prepaid voluntarily before maturity (as opposed to involuntary prepayment via the foreclosure process) as refinanced and focus on total refinancing regardless of prepayment reason – rate decrease or equity extraction. Berger, Milbradt, Tourre, and Vavra (2021) have shown that rate incentives are a crucial driver of refinancing decisions, even for households taking cash out of their homes. To control for refinancing incentives arising from variation in home equity alone, we construct current LTV ratio for each loan in our sample using ZIP-level house prices from the Zillow database in two steps. First, we calculate the value of the mortgaged property at origination by dividing loan amount at the time of origination by the LTV at origination. Second, we divide remaining loan balance by the value of the mortgaged property at origination.

Table 1 displays summary statistics (minimum and maximum observations, means, medians, and standard deviations) for key observable variables in our sample. Panel A displays mortgage characteristics at origination from our data set where the unit of observation is a loan (that is, one observation per loan), and Panel B displays summary statistics of the time-varying variables included in our analysis where the unit of observation is a loan-month (that is, multiple observations per loan).

We construct rate gap, $r^*_{it} - \hat{r}_{it}$, by calculating the difference between the current interest rate on the outstanding loan, r^*_{it}, and the predicted rate, $\hat{r}_{it}$, 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:

$$r_{it} = \alpha_0 + \alpha_1 CS_{it} + \alpha_2 CS^2_{it} + \alpha_3 LTV_{it} + \alpha_4 LTV^2_{it} + \alpha_5 DTI_{it} + \alpha_6 DTI^2_{it} + \alpha_7 r^m_t + \varepsilon_{it} \quad (1)$$

where for each borrower i with loan originated in t, CS denotes a FICO credit score, LTV denotes loan-to-value ratio, DTI denotes debt-to-income ratio, and r^m_t denotes the 30-year FRM average in the U.S. from Primary Mortgage Market Survey (PMMS) by Freddie Mac.[9]

Table 2 displays estimation results of regression (1) and shows that coefficients are consistent with previous findings in the literature. Borrowers with higher credit score, lower LTV, and lower DTI ratio tend to have lower mortgage rates. This specification

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

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

[9] Retrieved from FRED, Federal Reserve Bank of St. Louis at https://fred.stlouisfed.org/series/MORTGAGE30US.

explains about 90 percent of variation in outstanding mortgage rates.

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. Panel B of Table 1 shows that the average mortgage rate for contract in our sample (5.08) is close to the market 30-year FRM average (5.25). In Appendix A1 we show that the time series of mean mortgage rate for contracts in our sample is in line with the market 30-year FRM average. The average refinance rate is 1.53 percent per month which is comparable to 1.5 percent in Berger, Milbradt, Tourre, and Vavra (2021) for the period from 1992 to 2017.

Figure 2 plots Kaplan-Meier estimates of the unconditional average monthly rates of refinancing for lower (blue line) and upper (orange line) quartile credit score borrowers, with their 95% confidence bands, as a function of loan age.[10] The unconditional refinancing rate for upper quartile credit score borrowers is up to 0.6 percentage points higher than those for lower quartile.

3 Empirical Results

In this section, we show that the refinancing response to monetary policy depends on the distribution of borrowersâ credit scores. Our analysis comprises three steps. We start by providing visual evidence suggesting that credit score distribution affects refinancing and is a potential source of heterogeneity. Next, motivated by this observation, we find significant differences in refinancing across borrowers in different credit score quartiles, even after controlling for the rate gaps and other borrower characteristics. Finally, we estimate the effect of credit score heterogeneity on refinancing response to monetary policy and establish that refinancing differences across borrowers with different credit scores are explained by their differential sensitivities to mortgage rates.

3.1 Credit Score Distribution as a Source of Heterogeneity

To claim that refinancing depends on credit score distribution, we present visual evidence suggesting that (i) unconditional refinancing rate is higher for borrowers with higher credit scores, (ii) borrowers with higher credit scores are the ones who refinance most actively, and (iii) credit score distribution is time-varying. Time-varying credit score

[10] Loan age corresponds to number of months since mortgage origination.

distribution implies that refinancing opportunities are state-dependent (in this case, the state being time).

In Figure 2 we plot unconditional monthly refinancing rate for lower (blue line) and upper (orange line) quartile credit score borrowers over our sample period. The figure suggests that during several episodes of loose monetary policy – quantitative easings QE1 and QE2, refinancing rate is higher for borrowers with higher credit scores.

Next, we turn to the single loan cohort dynamics and conclude that borrowers with a higher credit score are the ones who refinance most actively. In the top panel of Figure 3, we plot the average mortgage rate of contracts outstanding that were originated in May 2000 and the current market mortgage rate. In the bottom panel of Figure 3, we plot the average credit score of contracts outstanding that were originated in May 2000. The average rate of outstanding loans in this cohort does not vary much, while their holders' average credit score is dropping, suggesting that borrowers with a higher credit score are more likely to refinance. Single cohort dynamics are similar for other cohorts – in Figure 4, we provide average mortgage rate and average credit score of contracts outstanding that were originated in May 2009.

To claim credit score state-dependence, besides the latter observations, one would also need to see the change in the consumer's credit scores over time. Figure 6 suggests that this is indeed the case. Over the last 20 years, the average credit score of borrowers in the lower quartile has increased by around 40 FICO points, whereas that of the borrowers in the upper quartile by only 20 points. Figure 7 confirms that time-varying credit score distribution is not an artifact of our sample – market credit score distribution from New York Fed Consumer Credit Panel and Equifax varies over time.

Figures 8, 9, and 10 display distributions of credit score, DTI, and LTV in the few years before (gray lines) and the few years after (purple lines) the financial crisis. While all three figures suggest that the credit constraints have tightened after the crisis, the fraction of households from our sample with credit score above 740 is much higher in after-crisis period.

3.2 Positive Relationship between Refinancing and Credit Score

In this subsection, we show a substantial positive correlation between refinancing and credit score after controlling for rate gaps and other borrower characteristics. We do so by constructing refinancing hazards by rate gaps for each credit score quartile.

We start by looking at refinancing, pooling all monthly observations for contracts that were originated in 2000–2019. For each outstanding loan i in month t we define the rate gap as $gap_{it} = r^*_{it} - \hat{r}_{it}$, where r^*_{it} is the current interest rate on the outstanding loan and $\hat{r}_{it}$ is the predicted rate for a new FRM originated in period t given borrower/loan characteristics.

We then sort loan-months to 20 basis point 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:

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

where $1\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; $1\{\text{Refi}_{it}\}$ is a dummy for the gap bin of loan i in month t; $1\{CS^{bin}_i\}$ 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 refi or a rate refi, 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 11 shows the resulting monthly refinancing hazard given by the point estimates for coefficients $\beta + \gamma + \delta$ for borrowers with credit score in lower (blue line) and upper (orange line) quartiles with their 95% confidence bands. Two observations stand out. First, 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 the negative rate gap.[11] Second, positive-gap loans with FICO credit scores in the upper quartile have a 1 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 higher credit score borrowers tend to have lower LTV ratios, higher income, and/or smaller mortgage balances. Figure 12 shows that restricting our sample to households with LTV ratio below 65% and excluding observations during 2007 – 2011 when households were more likely to be unemployed, does not change our results materially. Figure 13 suggests that our result is robust to restricting our sample to

[11] Our results are in line with Berger, Milbradt, Tourre, and Vavra (2021).

mortgages with outstanding balance above \$100,000 (mean of our sample). In Appendix A2, we show that our result is robust to aggregation to the quarterly level.

Results of this subsection imply that the refinancing differences between lower and upper credit score quartile borrowers with positive rate gaps is robust to inclusion of other borrower characteristics, geographical fixed effects, loan duration and restricting sample to loans with substantial remaining balance.

3.3 Heterogeneous Response of Refinance to Mortgage Rates

In this subsection, we show that the large differences in refinancing probabilities between different credit score groups can be explained by their differential sensitivities to mortgage rates. To establish that the lower credit score borrowers are less likely or less able to refinance when rates decline, we employ linear probability models and estimate them at a monthly frequency. We start with the ordinary least squares (OLS) regressions and show that the significant correlation between refinancing and interaction of rate gap with credit score is robust to (i) inclusion of additional interaction terms, (ii) aggregation to quarterly frequency, and (iii) geographical aggregation. We then employ instrumental variable (IV) regression because some unobserved variables (such as the state of the economy, borrower's financial literacy, etc.) may affect rate gaps, credit score sensitivities to rate gaps, and refinancing. We instrument rate gaps with high-frequency monetary policy shocks. High-frequency identification yields the unexpected part of the monetary policy shock because it controls for the market expectations by taking into account rate changes only within a small window

Our regressions take the following form: for the loan i at month t, we estimate

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

where $1\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; $gap_{it} = r^*_{it} - \hat{r}_{it}$ 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. In some specifications we include geographic fixed effects and origination year-month fixed effects. The standard errors are double clustered on 3-digit ZIP-code and month level. All variables except interest rate gap are normalised around corresponding sample means. All coefficients were multiplied by 100 to arrive to percentage changes.

Our specification controls for many observable variables that affect both refinancing and rate incentives. The main object of interest is the heterogeneity of refinancing response to monetary policy that affects market mortgage rates. Its extent is given by coefficients β in front of the rate gap and δ in front of the interaction between credit score and rate gap. This interaction captures the possibility that credit score which affects refinancing also varies with rate gaps. For example, borrowers with lower credit scores might be more likely to have both larger rate gaps and lower refinance probabilities.

3.3.1 Quantifying Credit Score Differences in the Sensitivity of Refinancing to Rate Gaps

We begin by quantifying credit score differences in the sensitivity of refinancing to gaps δ by running the OLS specification of equation (3). The estimation results are provided in Table 3.[12] 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 rate gap and credit score are in line with previous findings of the literature on FRM channel. A 1 percentage point increase in rate gap is associated, on average, with a 0.84 percentage points higher probability to refinance. Borrowers with a 1 standard deviation above mean credit scores are 0.08 percentage points more likely to refinance.

Recall that the rate gap is constructed using predicted rate for each borrower given their characteristics for FICO, OLTV, and DTI. If differences in refinancing between lower and higher credit score borrowers are explained to their differential sensitivities to rate gaps, then coefficient before interaction term should be positive. This is confirmed in column (2) of Table 3, which shows that higher credit score borrowers are significantly more likely to refinance in response to rate gap increase. A 1 percentage point increase in rate gap is associated with a 1.2 percentage points increase in the probability to refinance for borrowers with credit score 800 (one standard deviation above mean credit score) but only a 0.64 percentage points increase for borrowers with credit score 700 (one standard deviation below mean credit score).

[12] Note that significance levels of 10%, 5%, and 1% in all of the tables were adjusted 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 significance level according to the formula $\alpha_{stan} = \alpha / \sqrt{N/100}$.

To determine whether differential sensitivities to rate gap between lower and higher credit score borrowers arise due to variation in their observable characteristics, in column (3) of Table 3 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 rate gap remains significant and slightly increases. The coefficient on front of DTI has a positive sign suggesting that borrowers with higher DTI ratio are more likely to refinance.

In column (4) of Table 3 we estimate differential sensitivities to rate 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.

Finally, column (5) of Table 3 contains a full set of year-month-by-ZIP fixed effects. The inclusion of year-month fixed effects means that identification occurs entirely from ZIP-code variation rather than aggregate time-series variation within month.[13] This eliminates concerns that results might be driven by endogenous monetary policy since monetary policy does not vary across regions. Moreover, the year-month-by-ZIP-code fixed effects fixed effects guarantee that identification comes from ZIP-code-specific monthly variation within month and not from time-invariant regional differences. This eliminates concerns that results might be driven by differences in demographics, lender concentration or any other slower moving local characteristics. Controlling for these fixed effects decreases sensitivities to rate gap between lower and higher credit score borrowers by a fifth in absolute magnitude, from 0.3 to 0.24. Note that it also makes the coefficient in front of DTI insignificant. Comparison of columns (2) and (5) suggests that inclusion of all observable characteristics and time-by-location fixed effects decreases sensitivities to rate gap between lower and higher credit score borrowers only by 9% in absolute magnitude, from 0.27 to 0.24.

Results from Table 3 suggest that credit score is another source of refinancing het-

[13]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).

erogeneity in addition to rate gap. In Section 3.1 we have seen that the distributions of other borrower characteristics, LTV and DTI, have also shifted after the financial crisis even though not as much as that of credit score. It might be the case that these factors that affect refinancing also vary with rate gaps similarly to credit score. For example, borrowers with lower credit scores, higher DTI ratios or higher LTV ratios might be more likely to have both larger rate gaps and lower refinance probabilities.

We test whether there is heterogeneity of refinance to rate gap across other borrower characteristics by including additional interactions to our main specifications. Column (1) of Table 4 corresponds to specification in column (5) in Table 3, which includes all controls as well as origination year-month and a full set of year-month-by-ZIP fixed effects. In column (2) of Table 4 we add interaction of rate gap with LTV ratio. The addition of this interaction does not materially change our estimate for the rate gap sensitivity between different credit score borrowers. Its sign is positive but small in magnitude. One possible reason for unintuitive sign is that borrowers with higher LTV ratios and large rate gaps are also the ones with higher remaining balances. This specification omits interaction of gap with remaining balance and leads to an upward bias of the coefficient.

In column (3) of Table 4 we add interaction of rate gap with the DTI ratio. Its sign is negative but small in magnitude suggesting that borrowers with DTI ratio of 45% (one standard deviation above mean DTI) are 0.04 percentage points less likely to refinance than borrowers with DTI ratio of 35% (one standard deviation below mean DTI).

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

Overall, results from Table 4 suggest that inclusion of these additional interactions have not affected 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.

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

Table 5 is the quarterly version of Table 5. The key difference between the two is that the interest rate gaps, LTV, remaining balance, and the 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 1 percentage point increase in rate gap is associated with a 2.1 percentage points increase in the quarterly probability to refinance for borrowers with credit score 800 (one standard deviation above mean credit score) but only a 1.13 percentage points increase for borrowers with credit score 700 (one standard deviation below mean credit score). In column (2) we include underwriting characteristics and ZIP-code fixed effects, and 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. Addition of a full set of year-quarter-by-ZIP-code fixed effects in column (3) only slightly decreases credit score sensitivity to rate gap, from 0.49 to 0.44 in absolute magnitude.

In Table 6 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 ones obtained using loan-level variation. The specification with a full set of controls in column (3) implies that the credit score sensitivity to rate gap is 0.20, which is close to its loan-level counterpart of 0.24 from column (5) of Table 3.

3.3.2 Causal Effect of Rate Gaps on Refinancing

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

We re-estimate equation (3) using a monetary policy shock as an instrument for interest rate gap and 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 due to unobserved confounding factors.

We construct two measures of monetary policy shocks using high frequency identification approach which are based on Federal funds futures rates, Eurodollar futures rates and Treasury yields. High-frequency identification controls for 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 Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect 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 the first measure of monetary shocks, we closely adhere to the methodology of Swanson (2021), which is an extension of Gürkaynak, Sack, and Swanson (2005), 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 June 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 futures contracts at horizons of 2, 3, and 4 quarters, and 2-, 5-, and 10-year Treasury yields. The daily data is from the Bloomberg terminal. The dates and times of FOMC meetings up to 2004 are from the appendix to Gürkaynak, Sack, and Swanson (2005) and the dates of the remaining FOMC meetings are from Nakamura and Steinsson (2018) and Swanson (2021).

In line with Swanson (2021), we interpret the three estimated factors 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. The sign of the first factor 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, 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 easing.[14] Each factor is normalized to have a unit standard deviation. For all the details on high-frequency shock construction see Appendix A4.

The second measure of monetary shock is defined as the change in the 2-year Treasury yield in a 1-day window around scheduled FOMC announcements.

We begin by providing evidence that both shocks are plausible instruments for the mortgage rate gap. Table 8 provides first-stage regression estimates for each of the instruments, with Panel A corresponding to the first measure of monetary policy shock, and Panel B corresponding to the second measure. In both cases, we reject the null hypothesis of underidentification based on Kleibergen-Paap rk LM statistic for robust errors. We also reject the null of weak instruments based on Kleibergen-Paap Wald rk F statistic.

Point estimates in Panel A of Table 8 suggest that forward guidance and LSAP factors have larger effects on the mortgage rate as compared to federal funds rate. A 1 percentage point increase in the current federal funds rate target leads to 19 basis points decrease in the rate gap. A 1 percentage point increase in the expected federal funds rate one year ahead leads to 85 basis points decrease in the rate gap. Finally, a $215 billion surprise LSAP announcement leads to 2.66 basis points increase in the rate gap.[15]

Point estimates in Panel B of of Table 8 imply that a 1 percentage point monetary policy shock increases the rate gap by 56 basis points. Overall, estimates for both instruments are consistent with those from Eichenbaum, Rebelo, and Wong (2022) and Gertler and Karadi (2015).

Table 9 displays the results from estimating equation (3) separately using OLS and IV approaches with two different instruments described above. All these specifications include age controls 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. We start by outlining results for the model without underwriting characteristics in columns

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

[15] Coefficients in Panel A of Table 8 are in basis points per standard deviation change in the policy instrument. The standard deviation of the fed funds rate factor is 8.39 basis points, of forward guidance is 5.68 basis points, and that of LSAP around $215 billion (which corresponds to a roughly 15 basis point decline in the 10-year Treasury yield). See Swanson (2021) for details. Therefore, to compute effects of a 1 percentage point change in the current federal funds rate target, one needs to multiply coefficient by 100bp/8.39bp $\approx$11.92. To compute effects of a 1 percentage point change in the expected federal funds rate one year ahead, one needs to multiply coefficient by 100bp/5.68bp $\approx$17.61.

(1), (3), and (5). Both instrumental variable specifications yield similar results in absolute magnitude and confirm that OLS estimates for coefficients of gap and interaction of gap with credit score have downward bias. The estimate of sensitivity to rate gap changes from 0.21 to 0.39 when using instrumental variable approach. In columns (2), (4), and (6) we add underwriting characteristics. The addition of these controls slightly decreases IV estimates for the gap sensitivity from 0.39 to 0.37 for the first instrument, and from 0.39 to 0.36 for the second one. However, these estimates remain highly significant and around 1.5 higher than OLS counterpart in absolute magnitude.

Both IV specifications suggest that credit score heterogeneity has economically significant effects on refinancing. Column (3) suggests that the marginal impact of a one standard deviation increase in credit score is 0.37 percent, which amounts to 27% of the average monthly refinancing rate of 1.35 percent.[16] Another way to see it is as follows. Assume that all independent variables in regression are equal to their sample averages and that average credit score is initially equal to its mean of 750. The unconditional average share of mortgages that refinance is equal to 1.35 percent. The estimates of coefficient β imply that a 100 basis point decrease in mortgage rate (corresponding to increase in rate gap) increases the share of refinanced loans to 2.435 percent.[17] If a 100 basis point decrease in mortgage rate occurs when the average credit score is one standard deviation above mean, the share of refinanced loans rises to to 2.803 percent.[18] Therefore, the marginal impact of a one standard deviation increase in credit score is 0.368 percent. Similarly, the estimates in column (6) imply the marginal impact of a one standard deviation increase in credit score of 0.356 percent.

Results of this section imply that while expansionary monetary policy increases refinancing propensities for all borrowers, it disproportionately affects borrowers with higher credit scores. A 1 percentage point increase in rate gap increases the probability to refinance by 1.45 percentage points for borrowers with credit score 800 (one standard deviation above mean credit score) but only 0.72 percentage points for borrowers with credit score 700 (one standard deviation below mean credit score). Therefore, in response to monetary expansion, refinancing probability increases 2 times (1.45/0.72) more for borrowers with a FICO credit score of 800 compared to borrowers with a FICO score of 700.

[16] The average refinancing rate for the sample of FOMC months is slightly lower compared to the whole sample of 1.53% from Table 1.

[17] $1.35 + 1 \times \hat{\beta} = 2.435$.

[18] $1.35 + 1 \times \hat{\beta} + 1 \times \hat{\gamma} + 1 \times 1 \times \hat{\delta} = 2.803$. Note that the estimate for γ is not significant.

4 Model of Refinance

Since we do not observe borrowers' spending and wealth, we develop a FRM refinancing model which has two goals. Firstly: to show that credit score heterogeneity matters for monetary transmission to aggregate consumption, even after taking into account equilibrium effects of refinancing on lender income. Second: to demonstrate that credit score heterogeneity has economically significant distributional consequences.

Our continuous-time open economy model closely resembles a continuous-time open economy framework employed by Berger, Milbradt, Tourre, and Vavra (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 a FRM and are subject to aggregate interest rate risk. The mortgage rate in this model is a deterministic function of liquid short-term interest rate. Refinancing enters via a Calvo-style exogenous shock – households refinance at Poisson arrival times only if their rate gap is positive.[19]

The novel feature of our model is the means by which it integrates credit score heterogeneity: we assume that households' Calvo refinancing rates and liquid wealth borrowing limits correlate with their credit scores. We calibrate the probability of arrival of these refinancing shocks and borrowing limits to match the observed refinance rates and credit card limits by different credit score groups.

Our analysis focuses on comparing the effect of monetary policy on refinancing, average coupons, and consumption in the environments without and with credit score heterogeneity. We conclude that credit score heterogeneity dampens the effects of monetary policy by 10%.

[19] Note that Berger, Milbradt, Tourre, and Vavra (2021) models endogenous relationship between short and mortgage rates. We abstract from redistribution between borrowers and lenders and focus on partial equilibrium outcomes for two reasons. First, lenders have much lower marginal propensities to consume as compared to borrowers, significantly decreasing the impact of their returns on aggregate outcomes. Second, in our setting, such model would generate a counter-factual relationship between mortgage rate and refinancing: lower credit score borrowers would receive lower mortgage rates. Instead, we assume that mortgage rates do not depend on credit scores to highlight the effect of credit scores beyond mortgage rates.

4.1 Uncertainty

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

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

where Z_{it} 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 instanteneous variance (per unit of time) of log income, and η_y is is the mean reversion parameter.

Households face aggregate uncertainty because short-term interest rate follows a stochastic process. We model these interest rates using Cox, Ingersoll, and Ross (1985) model of interest rate:

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

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-term interest rate r_t, so that fluctuations in $m_t = m(r_t)$ arise from fluctuations in r_t in equilibrium.

4.2 Household Balance Sheet and Refinancing

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 that mortgages are never paid down to focus only on rate incentives for refinancing and abstract from cash-out refinancing. Even though refinancing incentives arising from house price movements are important, 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 household only at random, exponentially distributed attention 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 obtain opportunities to refinance at no cost at Poisson arrival times, and they exercise their option if and only if the current market interest rate m_t is below their outstanding coupon rate m_t^*.

Households can save or borrow in a liquid savings account W_t with return r_t to insure against labor income shocks. Thus, their liability is their outstanding mortgage, and payments on unsecured short-term debt if $W_t < 0$. Their net financial position is equal $W_t + r_t W_t 1\{W_t < 0\} - F$. Households do not have any option to default.

Credit score enters our model via differential arrival rates for refinancing shock and differential borrowing limits. Intuitively, credit score is a prediction of how likely household is to pay a loan back. If this probability is low, households cannot refinance mortgage and borrow more unsecured debt.

In the benchmark model without credit score heterogeneity, arrival intensity of refinancing shock χ and borrowing limit $b < 0$ is the same for all households. In the model with credit score heterogeneity, each household is born with (exogenous) credit score j which determines a Poisson arrival rate of χ_j of refinancing shock and borrowing limit b_j. There are no other differences between different credit score households.

Finally, we also assume that households face exogenous moving shocks that arrive at Poisson rate ν, forcing them reset their mortgage coupon to the current market mortgage rate m_t. This shock does not differ across different credit score borrowers.

Summary. The goal of our model is to provide a simple framework for analyzing the refinancing channel of monetary policy transmission in the presence of heterogeneity. Our partial equilibrium model has four state variables (W_i, r, m_i^*, Y_i). 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 provides a role for monetary policy.

4.3 Household Problem

Households with identical constant relative risk aversion preferences with rate of time preference δ and intertemporal rate of substitution $1/\gamma$ make consumption $\{C_t\}_{t\geq 0}$ and refinancing decisions $\{\rho_t\}_{t\geq 0}$ by solving the following problem:

$$\max_{C,\rho} E_0 \left[\int_0^\infty e^{-\delta t} \frac{C_t^{1-\gamma}}{1-\gamma} dt \right]$$

subject to

$$dW_t = (Y_t - C_t + r_t W_t - m_t^* F)dt,\ W_t \geq b_j \tag{6}$$

$$dm_t^* = (m_t - m_{t-}^*)\left[\rho_t dN_t^{(\tau_{refi})} + dN_t^{(\tau_{move})}\right] \tag{7}$$

and Y_t following (4), r_t following (5), and $m_t = \alpha_0 + \alpha_1 r_t$. Here τ_{refi} is the sequence of times when refinancing shock arrives, τ_{move} is the sequence of times the household is forced to move, and $N_t^{(\tau_{refi})}$ and $N_t^{(\tau_{move})}$ are changes in the corresponding counting processes.

Appendix A5 provides Hamilton-Jacobi-Bellman and Kolmogorov Forward equations. We solve the model numerically using the finite difference method.

4.4 Calibration

In this subsection we describe the model's calibrated parameters. These parameter choices are summarized in Table 10.

Our calibration of the income process follows **?**, who estimate 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 rate process with maximum likelihood estimation using daily data for 3-month treasury yields from 2000 to 2019, and obtain $\eta_r = 28$ 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 $\bar{r} = 4.1$ percent so that the corresponding initial model implied mortgage rate at the mean is equal to its empirical counterpart in 2019 when we start our experiments.See Appendix A6 for details on MLE estimation.

We calibrate the linear function parameters, α_0 and α_1, that relate market mortgage rates and short-term rates by regressing 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 \$225,230.

Discount parameter δ is calibrated to match median wealth (excluding home equity) of homeowners in 2019 from Survey of Income and Program Participation (SIPP) data. Main homeowners for our sample period are Millenials, Generation X and Baby Boomers. We weight their wealth according to house purchase shares from "2021 National Association of Realtors Home Buyer and Seller Generational Trends." to arrive to a median wealth of $48,362. This strategy requires δ=9 percent per annum, and generates an ergodic average liquid savings $E[W_t]$= $ 90,391.

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 set borrowing limit for this economy b to $30,000 corresponding to average average credit card limit in 2019, according to Experian.[20]

In the model with credit score heterogeneity, we assume that credit score j takes three values $j \in \{L, M, H\}$. We limit the model to three credit score groups – low, middle, and high – which occur with equal probability. We set $\chi_L = 0$ percent, restricting households from the lowest credit score group from refinancing. $\chi_M = 26.54$ percent, matching average refinancing rate for borrowers with positive rate gaps and FICO score below 75^{th} percentile in our data. We set $\chi_H = 54.49$ percent, so that average refinancing rates are the same in baseline and heterogeneous economies.

We calibrate borrowing limits in the heterogeneous economy in the following way. We assume that low credit score households cannot borrow and set $b_L = 0$, medium credit score borrowers can borrow up to $15,000, implying $b_M = -\$15,000$. Finally, to make the average borrowing limit equal between baseline and heterogeneous economies, we set $b_H = -\$45,000$.[21]

4.5 Steady State

The steady state in our setup features cross-sectional heterogeneity in three variables: W, m^*, and Y. Figure 15 plots the steady state consumption function for a baseline economy with no credit score heterogeneity. From left to right, each panel represents a different

[20] According to Experian, the average credit card limit in 2019 was $31,459. Altering limit from $30,000 to $31,459 does not change our results.

[21] It is common to calibrate the credit card borrowing limit to one third of permanent income. For example, Kaplan, Moll, and Violante (2018) calibrate a borrowing limit of one times quarterly labor income. This number is consistent with reported credit card borrowing limits in the Survey of Consumer Finances.

income state. Consumption is decreasing in outstanding mortgage rate and decreasing in wealth. In Figures 16, 17, and 18, we provide steady state consumption functions for each credit score group, which are qualitatively in line with the baseline setup.

Table11 summarizes the modelâs steady state. The first row lists average consumption. Average consumption is comparable across two economies, and is less than average income due to debt repayment. The second row lists average MPC out of liquid wealth. The baseline economy features average MPC of 0.33, and the heterogeneous economy - that of 0.37. Households in the low credit score group have highest MPCs with an average of 0.47, whereas these numbers are 0.36 and 0.27 for medium and high credit score groups. The final two rows summarize the accumulation of liquid wealth. In the baseline economy, 2.3% of households are at their borrowing limit. In the heterogeneous economy, this number is 2.4%. In the baseline economy more borrowers hold credit card debt as compared to the heterogeneous economy (6.3% vs. 5.4%).

4.6 Monetary Policy

Next we study the impact of stimulative monetary policy in economy with and without credit score heterogeneity. Starting from the steady state, interest rates are cut from 4.1% to 1.7% corresponding to 1% decline in market mortgage rate.

The top row of Figure 19 shows the impulse response functions (IRFs) of mortgage rate and average coupon in the baseline economy and economy with credit score heterogeneity. Mortgage rate is a linear function of interest rate and is the same for two economies by construction. Average coupon responds to monetary policy more strongly in the baseline economy. This is because the heterogeneous economy includes households who cannot refinance and, therefore, do not reset their mortgage rates.

The bottom row Figure 19 shows the IRFs of refinancing rate and consumption in the baseline economy and economy with credit score heterogeneity. Average refinancing rates in the two economies are calibrated to be the same, resulting in an almost identical on-impact response of refinancing. However, initial refinancing impulse declines faster in heterogeneous economy because refinancing shock arrives only to medium and high credit score groups, and exhausts the number of households with both ability and incentives to refinance.

Even though differences in refinancing are not large, consumption responds more to rate cuts in the baseline economy than in the heterogeneous economy. On impact the aggregate spending semi-elasticity is 140 bps in the baseline economy versus 125 bps in the heterogeneous economy, i.e. a 11 percent increase over the baseline.

Heterogeneous economy is less responsive to monetary policy because low credit score households, who cannot borrow and refinance, have highest marginal propensities to consume. To show that low credit score group has significantly lower consumption response than other groups, in Figure 20 we decompose refinancing and consumption response by credit score group. On impact, households in low credit score group increase their consumption by 101 bps, whereas medium and high credit score households respond much more – by 131 and 143 bps, i.e. by 30 percent and 42 percent more than low credit score households.

Overall, monetary policy in this economy affects household consumption through two channels. First, there is the standard wealth effect - the change in interest rate r_t affects the household's return on W_t. This wealth effect includes only substitution effect, and no income effect, since we abstract from effect of monetary policy on income in this setup. Intertemporal substitution effect of rate cut induces household to save less (or borrow more) and increase their demand for consumption. Second, the interest rate cut gives some households the option to refinance and reset their mortgage rate into a lower one, which frees up disposable income for more consumption.

To decompose the initial consumption response to monetary policy into its two components and see how credit score heterogeneity affects each, we isolate the wealth effect, by shutting refinancing down in both economies. This decomposition is displayed in Table 12. Each cell in the first row represents the on-impact consumption elasticity in the model without refinancing. In homogeneous economy, 15% of total consumption response can be attributed to the refinancing channel. In heterogeneous economy, where households have differential borrowing constraints, only 10% of total response is through the refinancing channel. The refinancing channel in low credit score group is 0 by construction, so increase in consumption for this group is driven by wealth effect only.

Credit score heterogeneity dampens both wealth and refinancing channels because medium and high credit score have lower MPCs than low credit score borrowers. First, the differential borrowing limits affect wealth channel of monetary transmission. The wealth effect is higher for medium and high credit score households compared to that for low credit score households. At the same time, the overall wealth effect is lower in the heterogeneous economy. This is because medium and high credit score households are able to borrow. Second, refinancing effect benefits higher credit score households by less than medium credit score households.

5 Conclusion

We have shown that credit score heterogeneity in the refinancing probability dampens monetary policy transmission through FRMs. Using Fannie Mae Single-Family Loan-Level historical data, we found that the effect of monetary policy on refinancing is heterogeneous across the credit constraints faced by the borrowers. In particular, a 1% expansionary monetary policy shock causes a 1.09pp average increase in probability to 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 credit score heterogeneity dampens the consumption response to monetary policy by 11% – refinance gains increase by less for borrowers with higher chances of refinancing. Credit score heterogeneity is another significant source of monetary policy heterogeneity besides mortgage rate heterogeneity.

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

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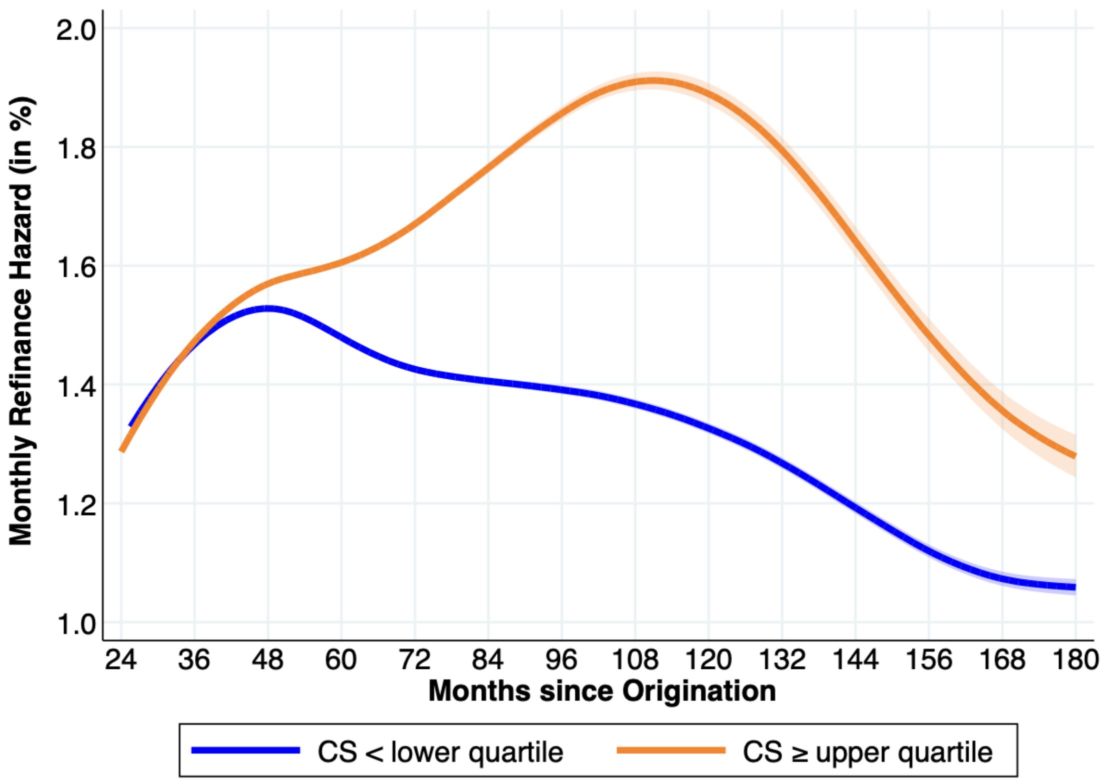
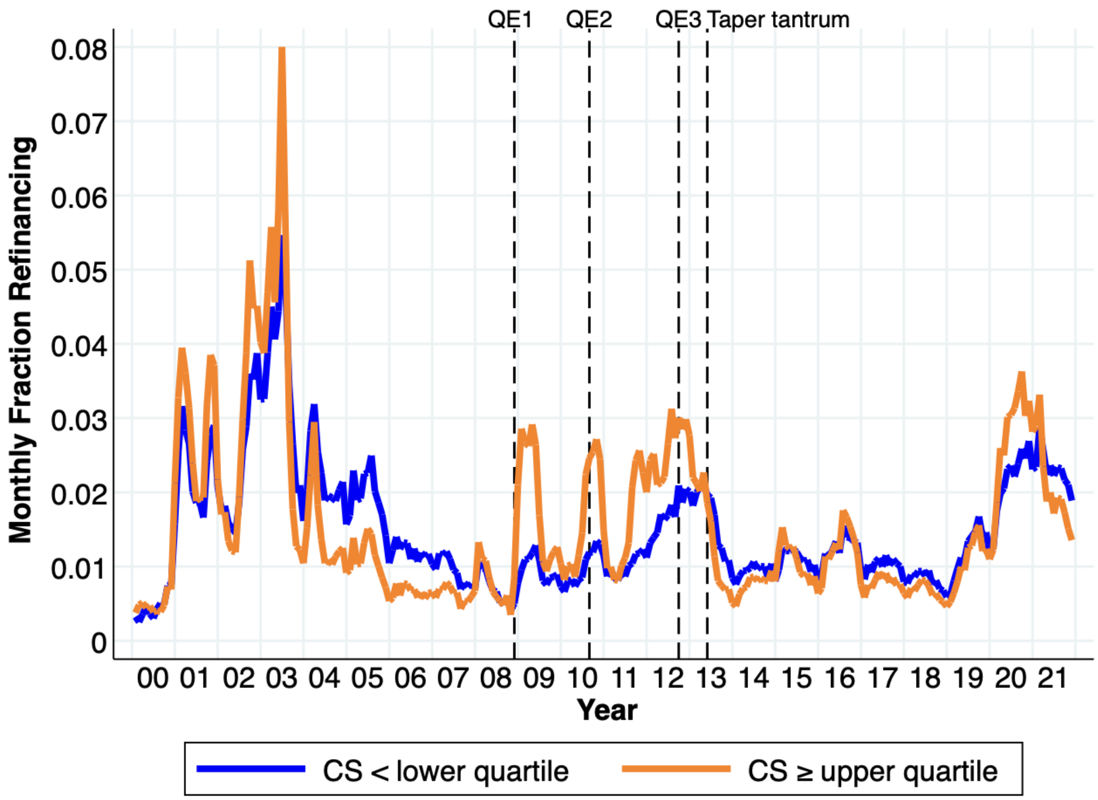
Figure 1: Smoothed Kaplan-Meier Unconditional Refinance Rates



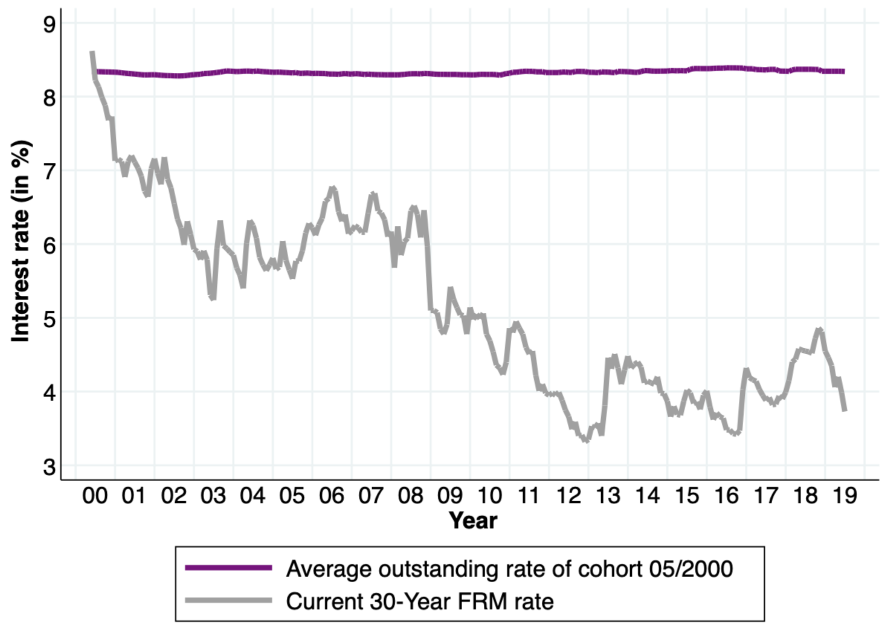
Notes: Figure shows the smoothed Kaplan-Meier hazard estimates of refinance broken down by FICO score quartiles and the corresponding 95% pointwise confidence bands. The Kaplan-Meier estimate of the hazard function is: $\lambda(t_j) = \frac{d_j}{n_j}$, where d_j is the number of mortgage terminations due to refinance at time t_j, and n_j is the number of loans that have reached time t_j without being terminated or censored. The smoothed hazard-function estimator was calculated using the Epanechnikov kernel and the optimal bandwidth. Figure uses the Fannie-Mae Single-Family Loan-Level historical dataset.

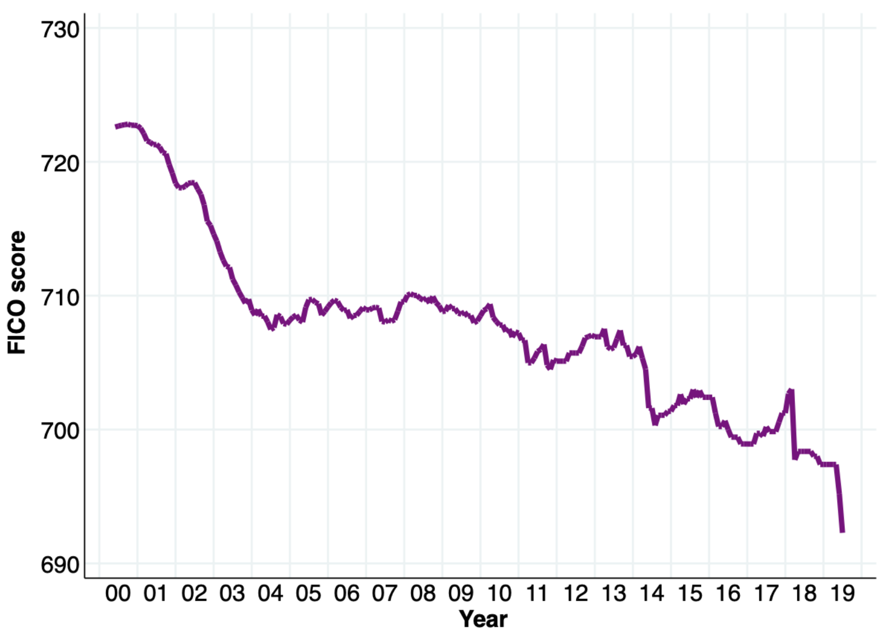
Figure 2: Unconditional Monthly Refinance Hazard for Lower and Upper Quartile Credit Score Borrowers



Notes: Figure shows monthly refinance hazard defined as the monthly fraction of loans that refinance. Events are QE1, annoucement of original LSAP in November 2008; QE2, Bernankeâs August 2010 speech suggesting an expansion of LSAPs; QE3, FOMC vote to buy $40b bonds per month in September 2012; Taper tantrum, Bernankeâs 2013 FOMC press conference suggesting that FOMC would wind down purchases of MBS. The data come from the Fannie-Mae Single-Family Loan-Level historical dataset.

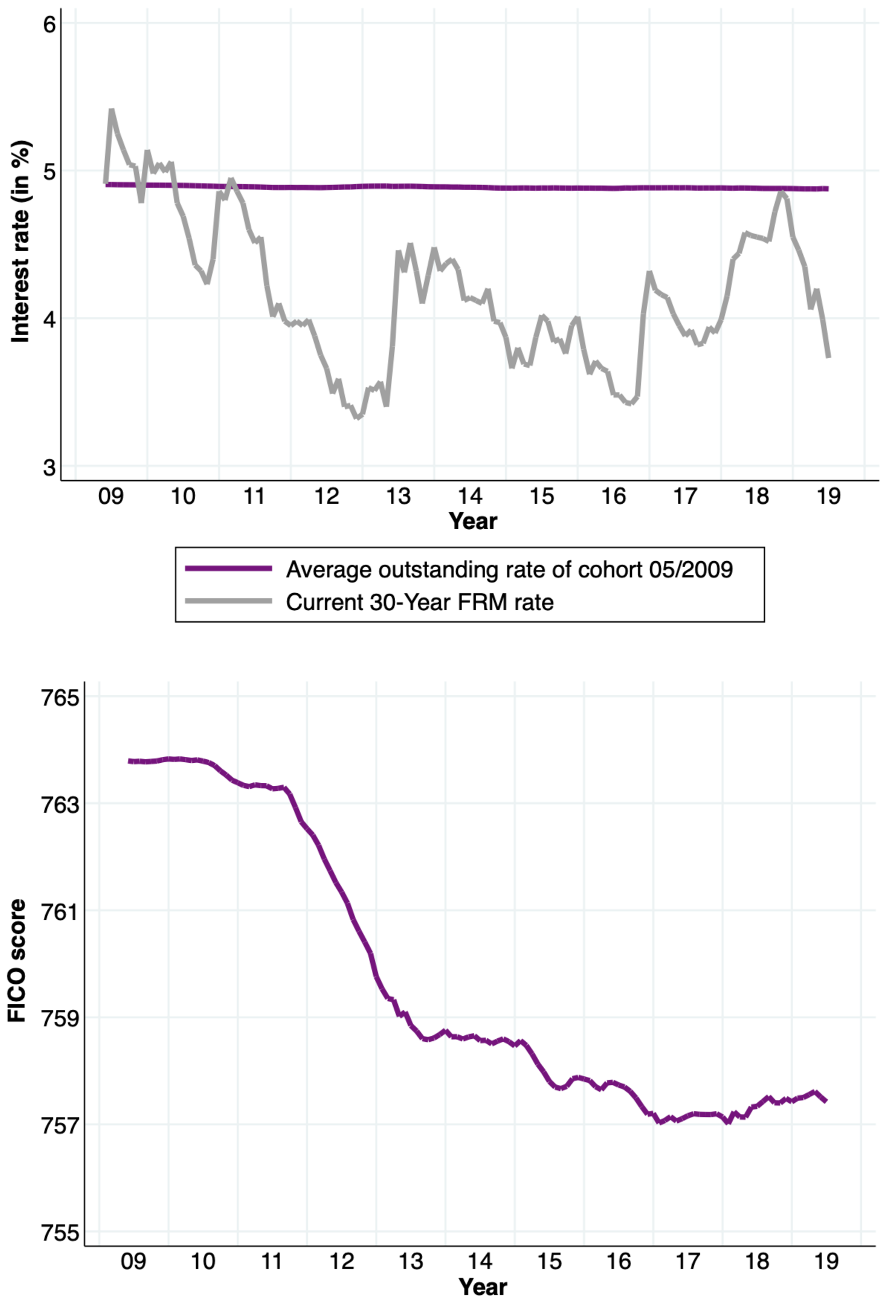
Figure 3: Outstanding and Current Market Mortgage Rates (top panel) and Average Credit Score of Outstanding Mortgages (bottom panel) on Mortgages Originated in 05/2000





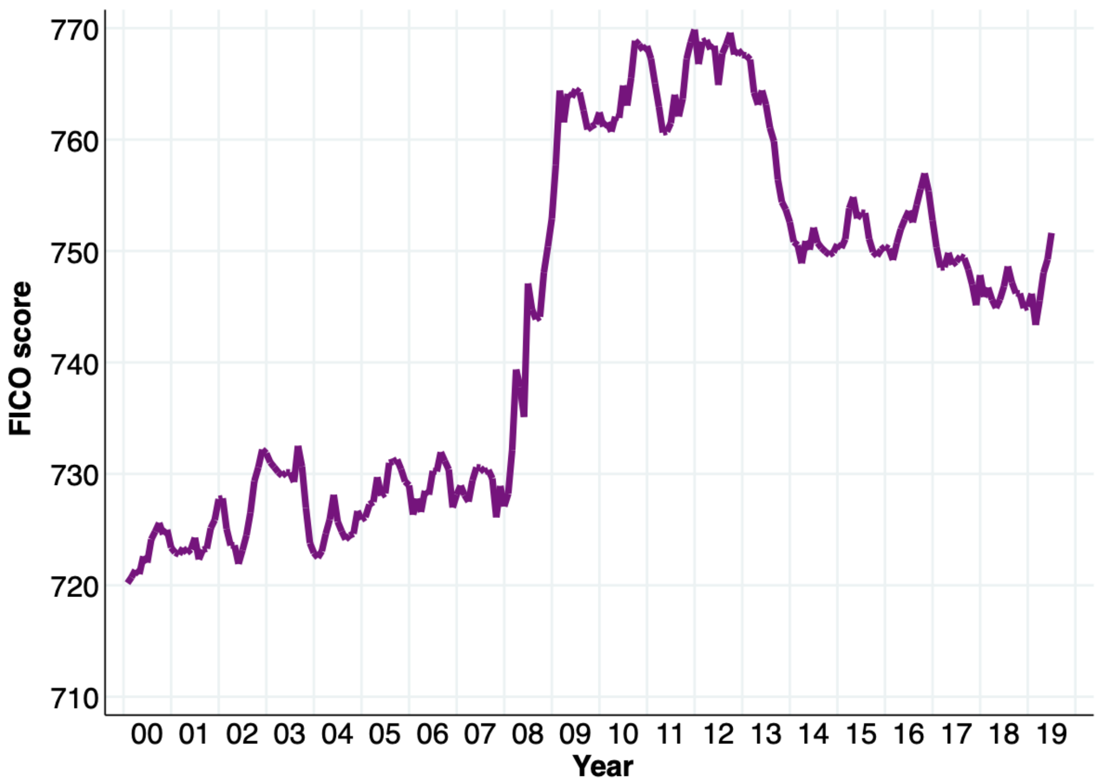
Notes: Figure shows the average outstanding mortgage rate along with market mortgage rate (top panel) and average credit score (bottom panel) on mortgages originated in May 2000. Data on the average mortgage rate and average credit score on mortgages originated in May 2000 comes from the Fannie-Mae Single-Family Loan-Level historical dataset. The market mortgage rate comes from FRED, Federal Reserve Bank of St. Louis at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

Figure 4: Outstanding and Current Market Mortgage Rates (top panel) and Average Credit Score of Outstanding Mortgages (bottom panel) on Mortgages Originated in 05/2009



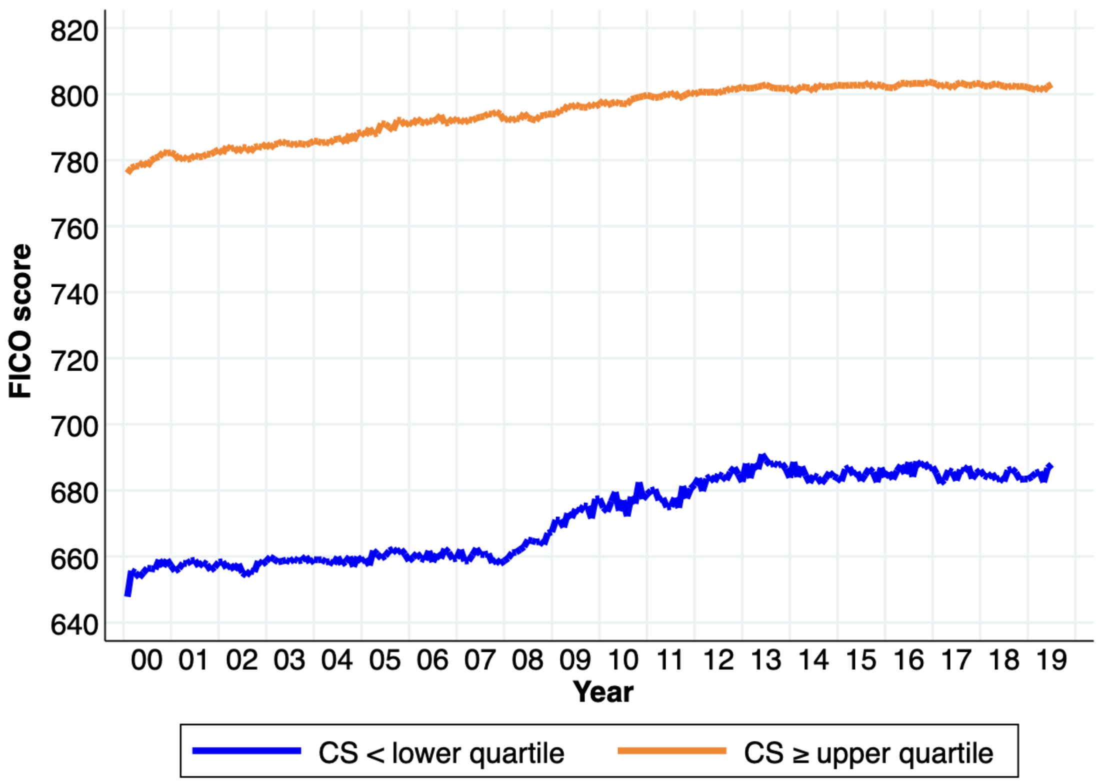
Notes: Figure shows the average outstanding mortgage rate along with market mortgage rate (top panel) and average credit score (bottom panel) on mortgages originated in May 2009. Data on the average mortgage rate and average credit score on on mortgages originated in May 2009 comes from the Fannie-Mae Single-Family Loan-Level historical dataset. The market mortgage rate comes from FRED, Federal Reserve Bank of St. Louis at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

Figure 5: Credit Score at Origination



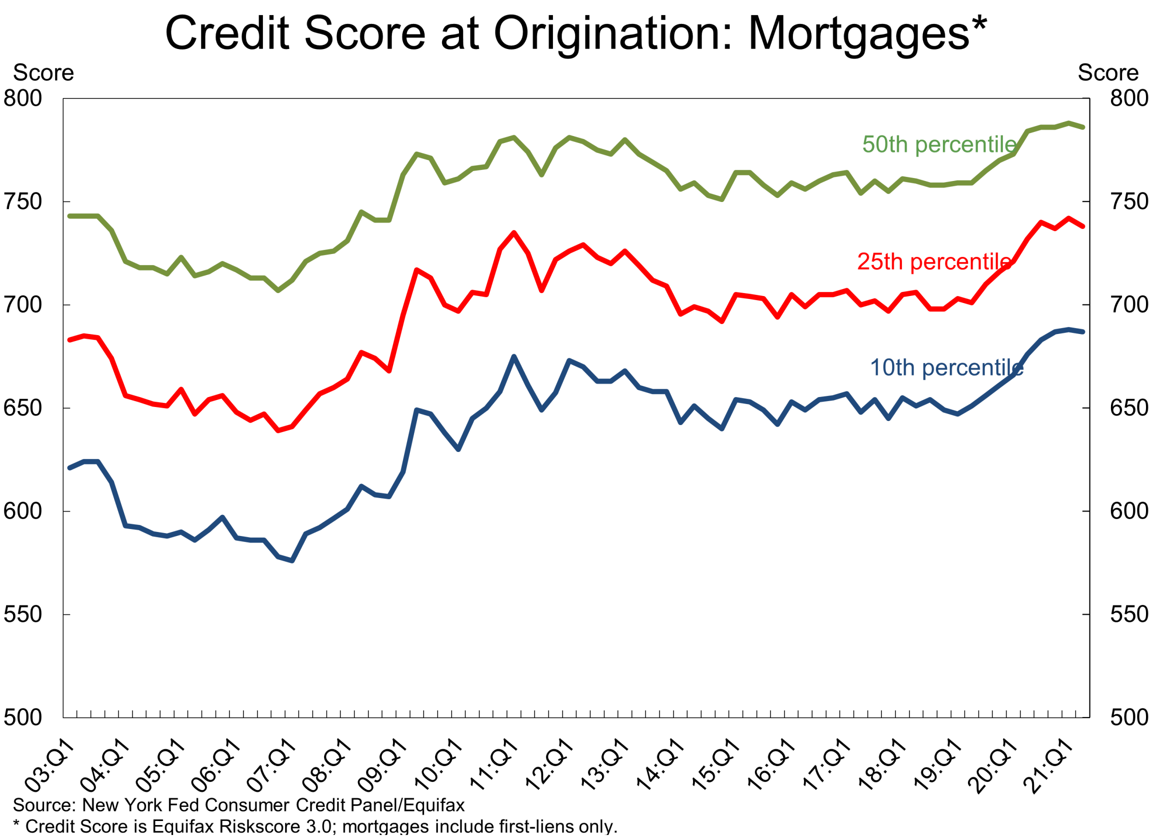
Notes: Figure shows the credit score at origination month (averaged across new borrowers) using the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 6: Credit Score at Origination for Lower and Upper Quartile Credit Score Borrowers



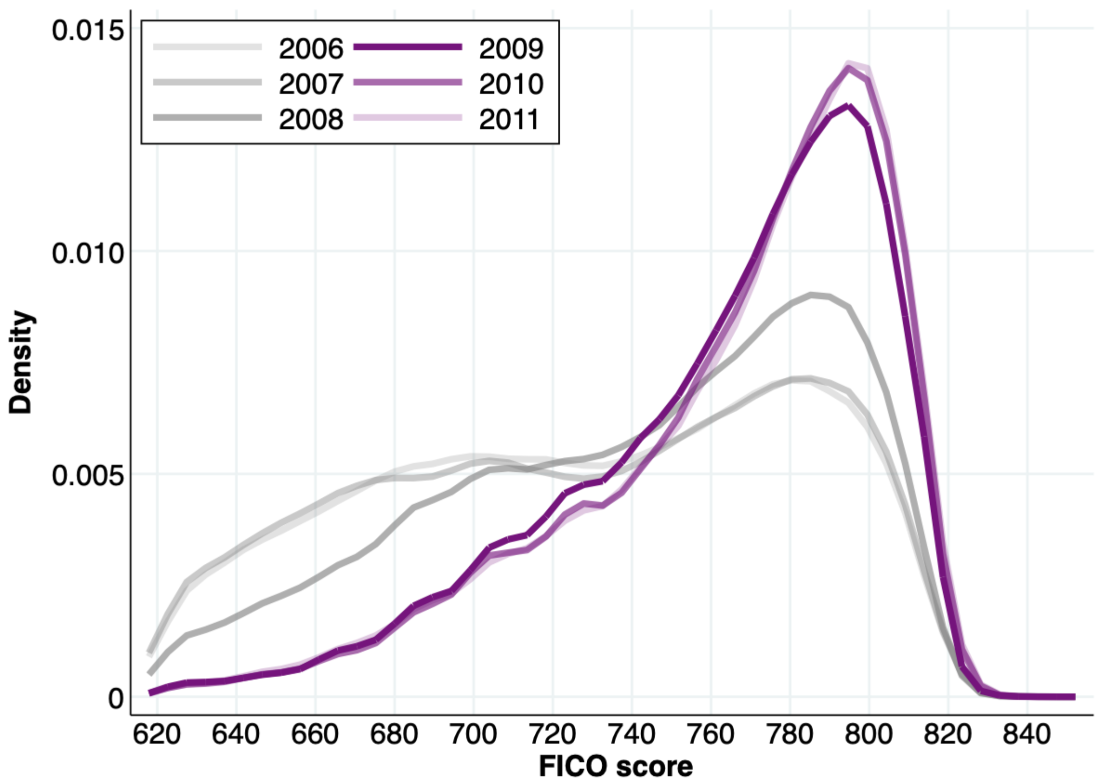
Notes: Figure shows the credit score at origination month (averaged across new borrowers) for borrowers in the lower and upper credit score quartile using the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 7: Distribution of Credit Score at Origination from New York Fed Consumer Credit Panel/Equifax



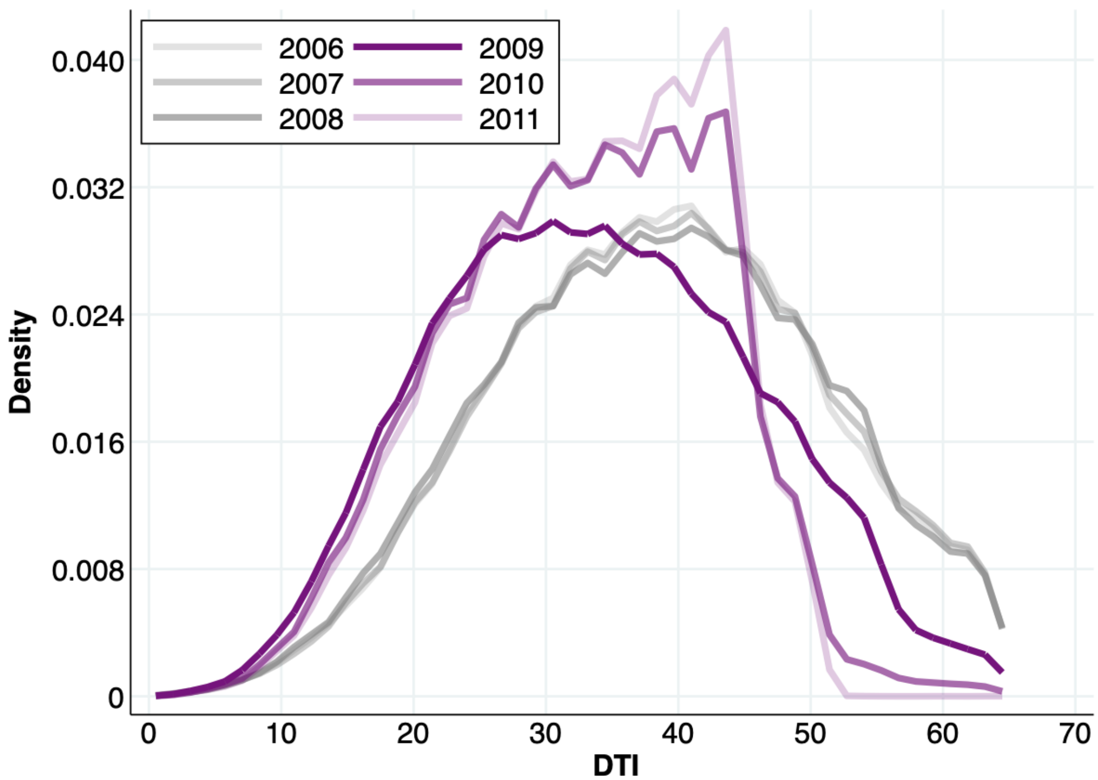
Notes: Figure shows the credit score at origination (averaged across new borrowers) for borrowers in 10th, 25th, and 50-th percentiles using data from New York Fed Consumer Credit Panel/Equifax

Figure 8: Distribution of FICO Score from 2006 to 2011



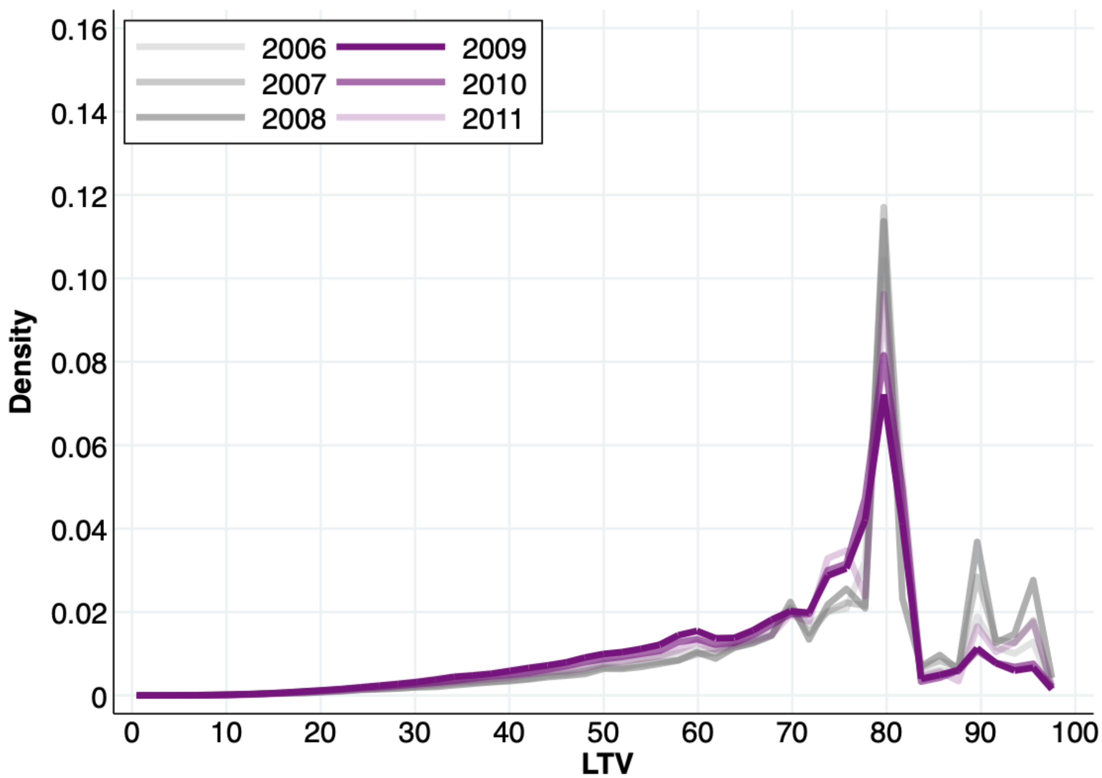
Notes: Figure shows distribution of FICO credit score at origination year using the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 9: Distribution of DTI from 2006 to 2011



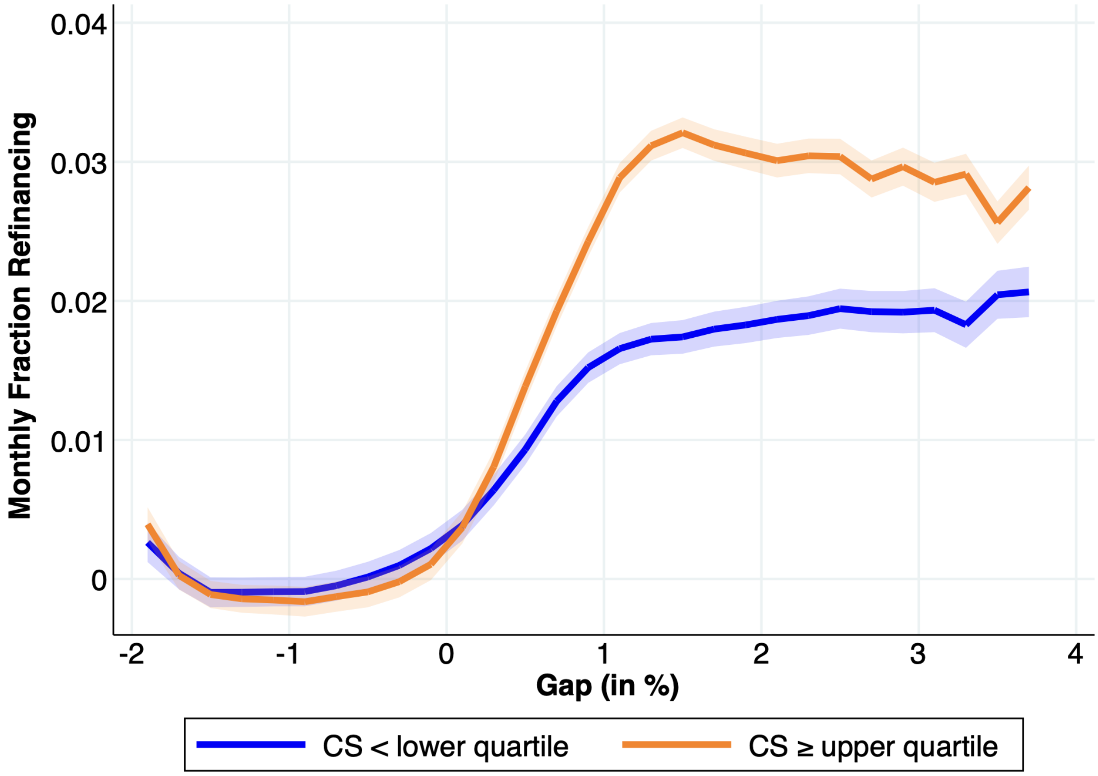
Notes: Figure shows distribution of DTI at origination year using the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 10: Distribution of LTV from 2006 to 2011



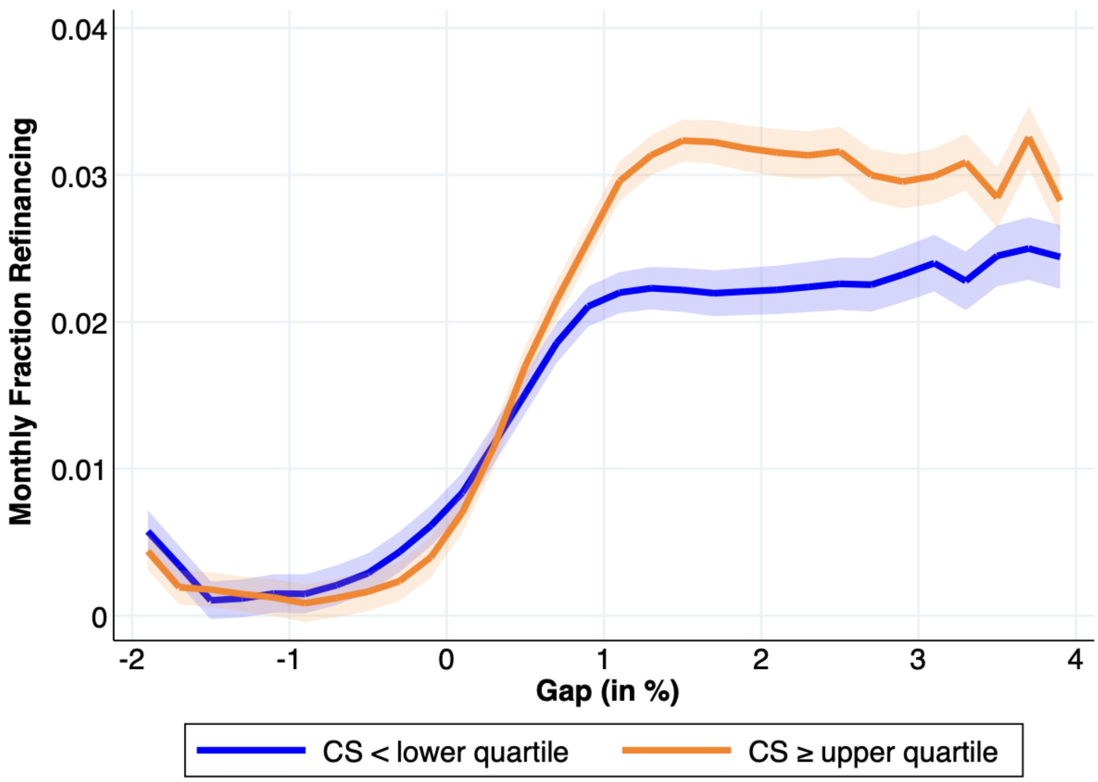
Notes: Figure shows distribution of LTV at origination year using the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 11: Refinance Hazard with Individual Controls for Lower and Upper Quartile Credit Score Borrowers



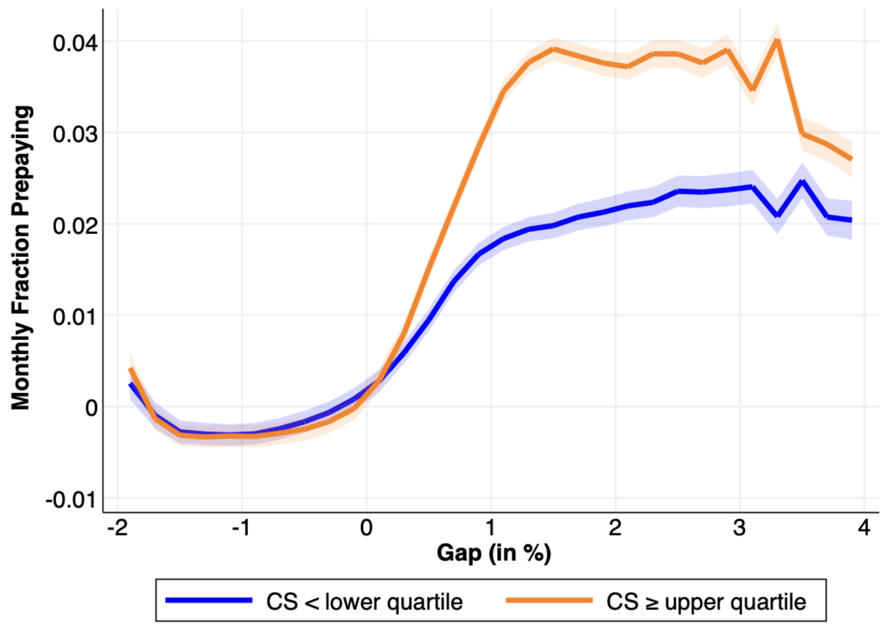
Notes: Figure shows point estimates for coefficients $\beta+\gamma+\delta$ on the 20bp bin dummies in regression (2) for borrowers in the lower credit score quartile (blue) and in the upper credit score quartile (orange). The estimation is performed at the monthly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-month. 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.

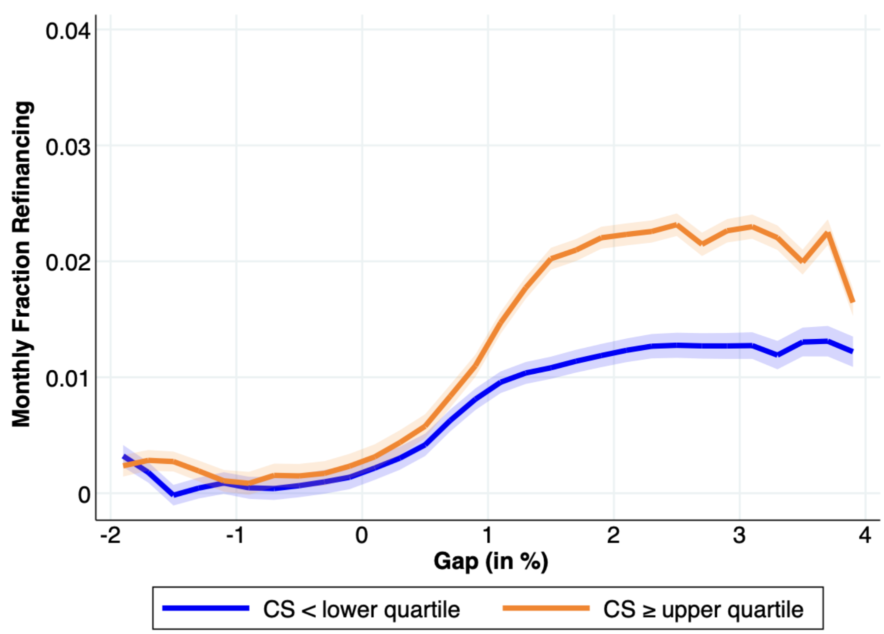
Figure 12: Refinance Hazard with Individual Controls: Low LTV Households



Notes: Figure shows point estimates for coefficients $\beta + \gamma + \delta$ on the 20bp bin dummies in regression (2) for borrowers with LTV < 65% in the lower credit score quartile (blue) and in the upper credit score quartile (orange). The estimation is performed at the monthly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The figure excludes data from the years 2007 to 2011. The unit of observation is a loan-month. 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.

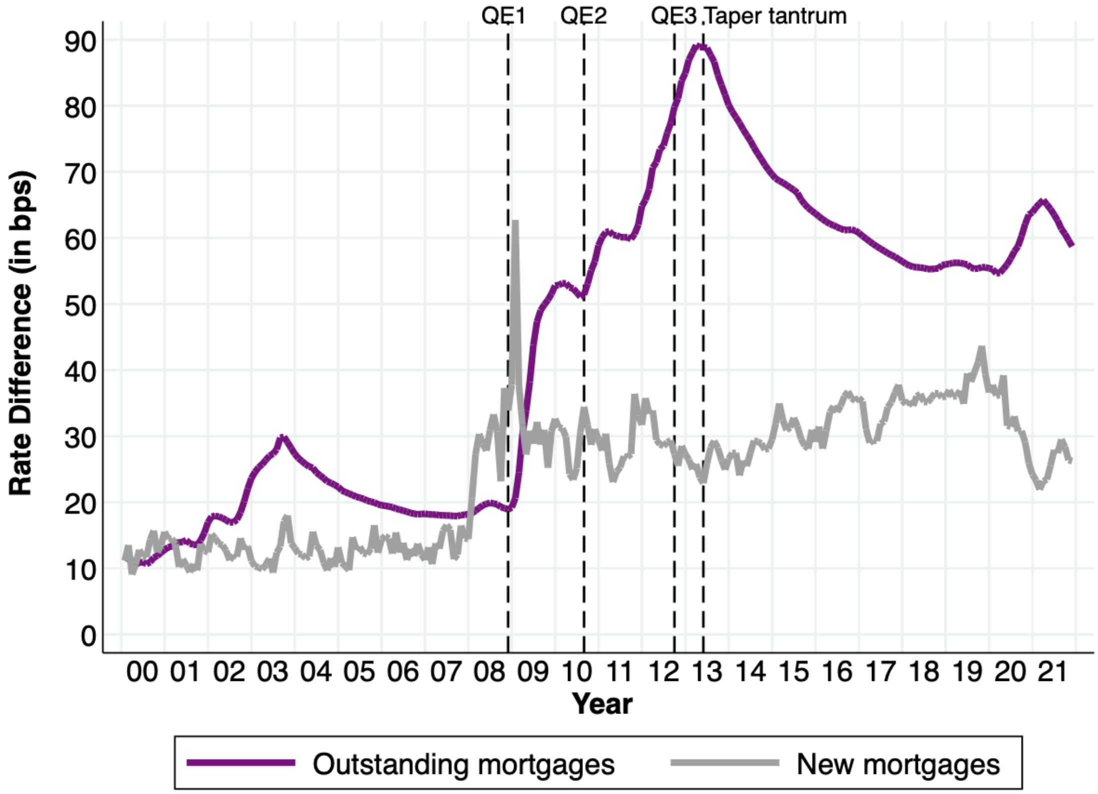
Figure 13: Refinance Hazard with Individual Controls for Mortgages with Mortgage Balances > $100,000 (top panel) and Mortgages with Mortgage Balances < $100,000 (bottom panel)





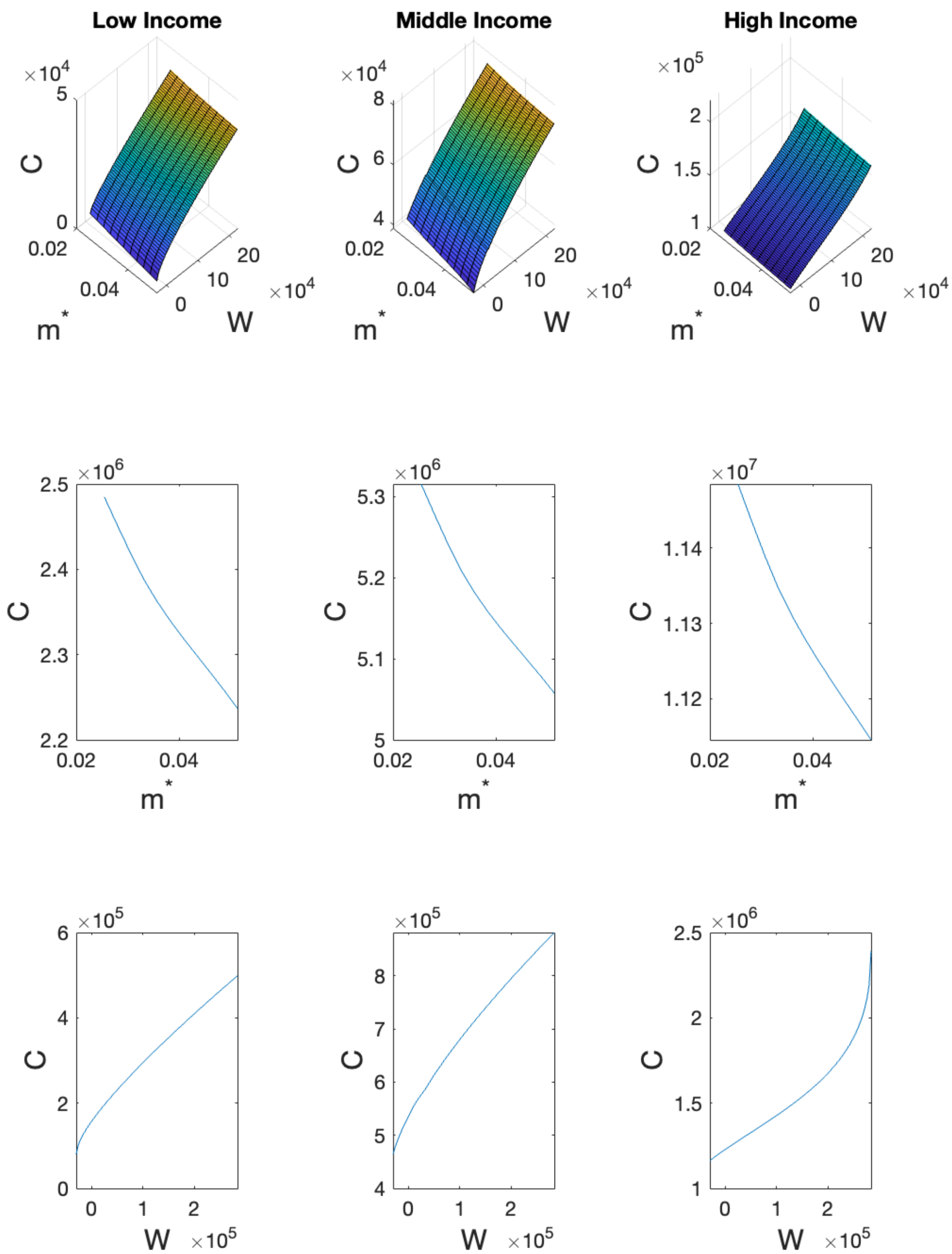
Notes: Figure shows point estimates for coefficients $\beta+\gamma+\delta$ on the 20bp bin dummies in regression (2) for borrowers with balances more than $100,000 (top panel) and balances more than $100,000 (bottom panel) in the lower credit score quartile (blue) and in the upper credit score quartile (orange). The estimation is performed at the monthly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-month. 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 14: Difference in Mortgage Rates of Lower and Upper Quartile Credit Score Borrowers



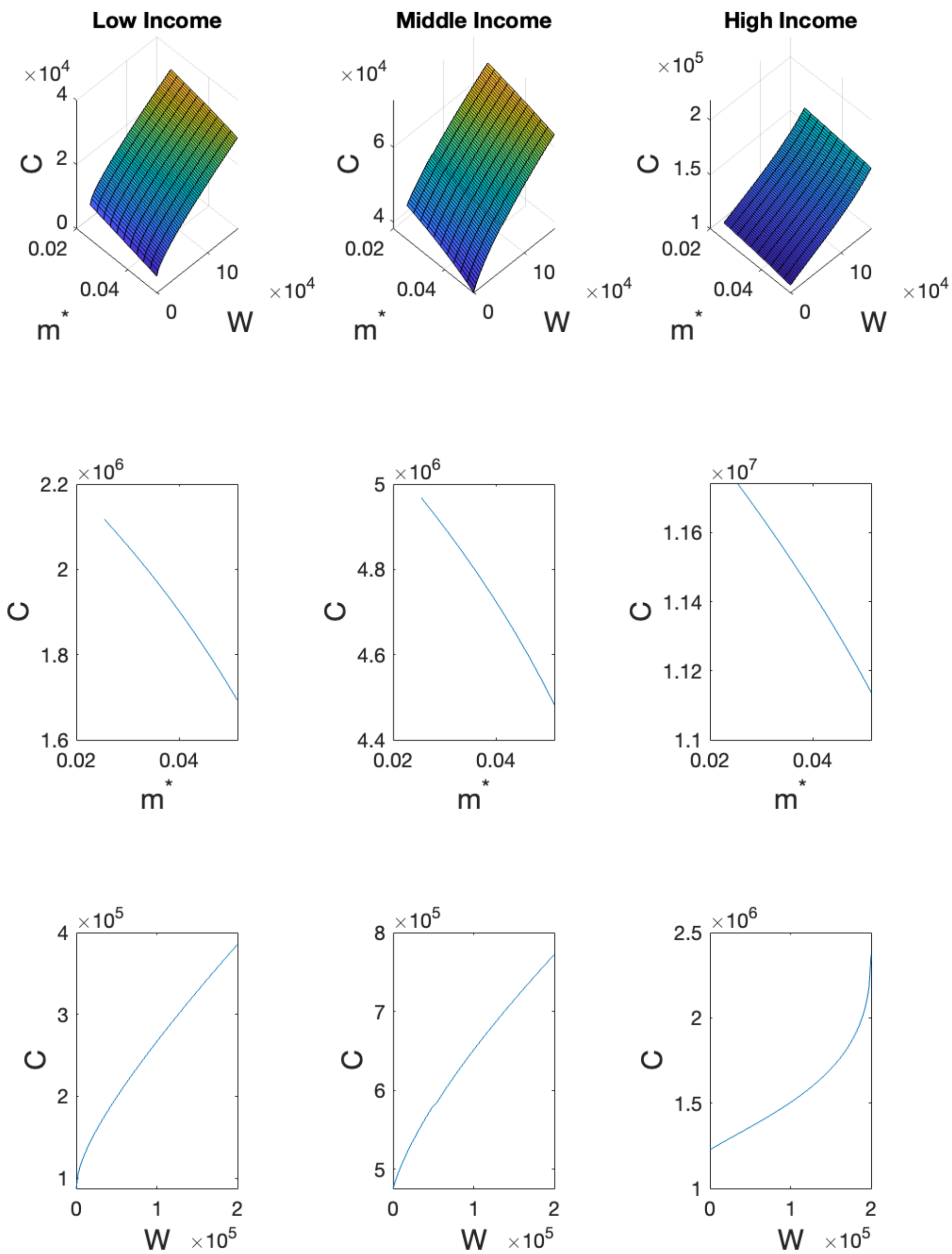
Notes: Figure displays the difference between the average mortgage rate paid by a lower versus an upper quartile credit score borrower. "New mortgages" are mortgages originated in the month. "Outstanding mortgages" are all mortgages outstanding in the month, including new mortgages. The data come from the Fannie-Mae Single-Family Loan-Level historical dataset.

Figure 15: Steady State Consumption Function in the Baseline Economy



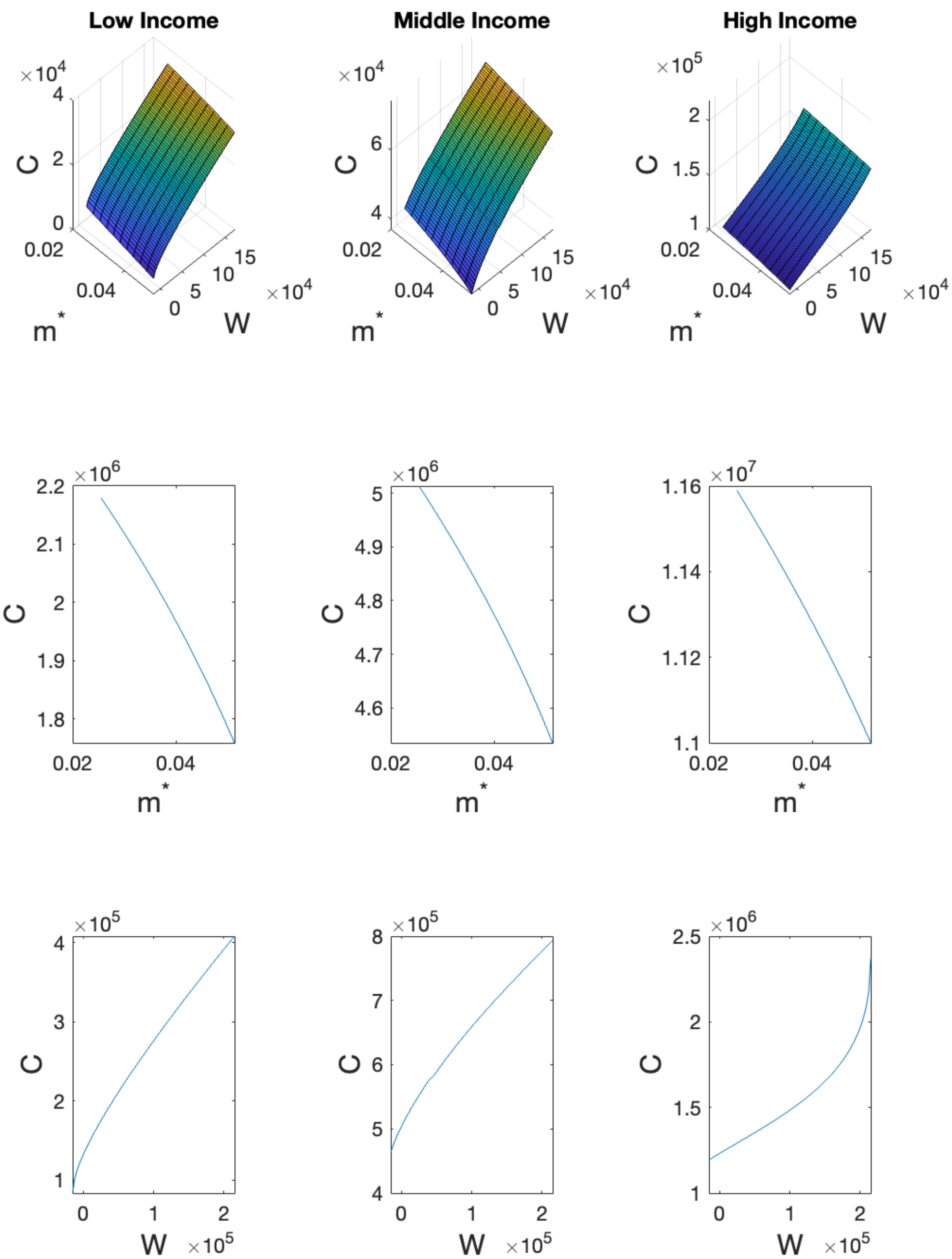
Notes: Figure displays steady state consumption as a function over income, outstanding mortgage rate, and liquid wealth. See text for details.

Figure 16: Steady State Consumption Function for Low Credit Score Households



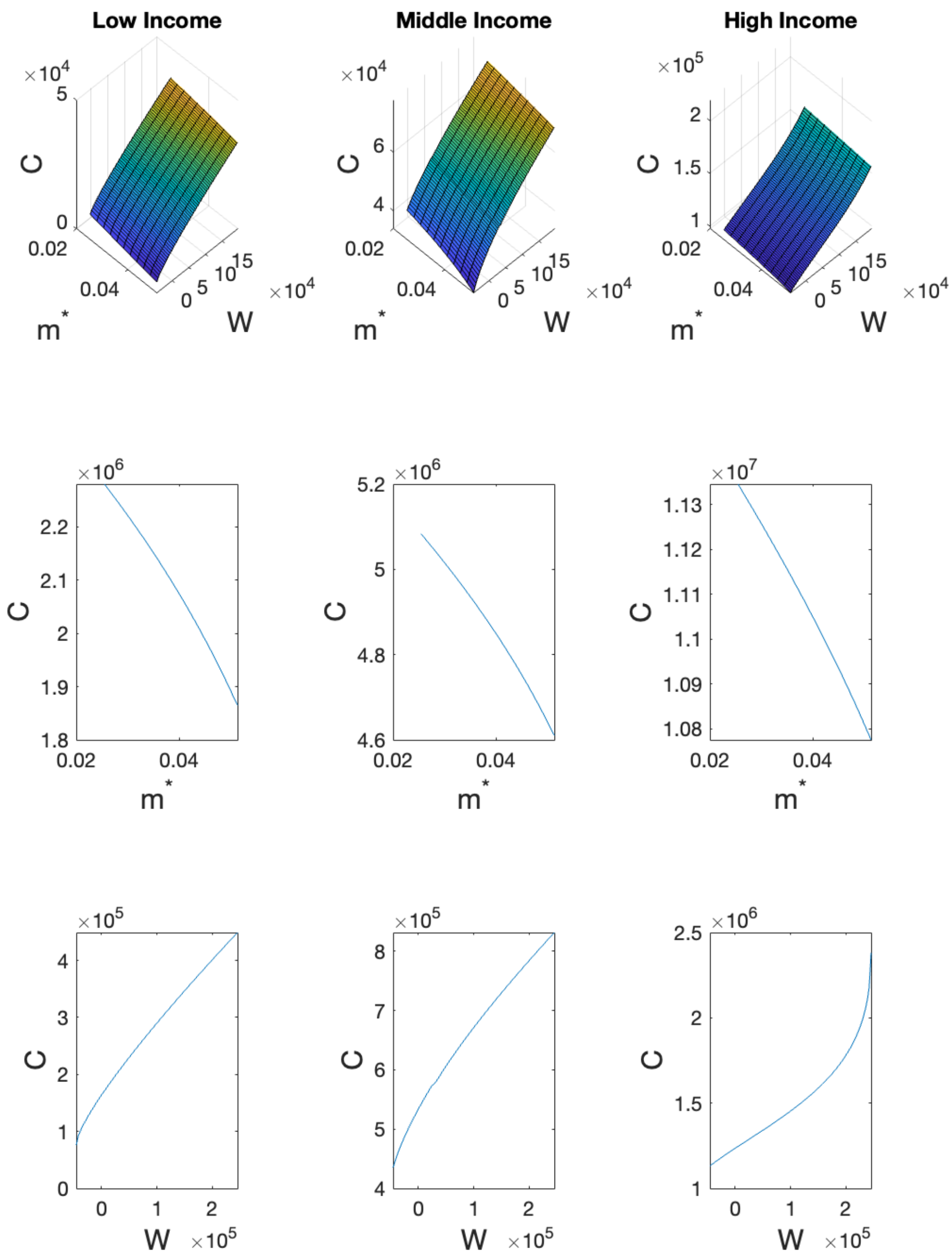
Notes: Figure displays steady state consumption as a function over income, outstanding mortgage rate, and liquid wealth for low credit score households. See text for details.

Figure 17: Steady State Consumption Function for Medium Credit Score Households



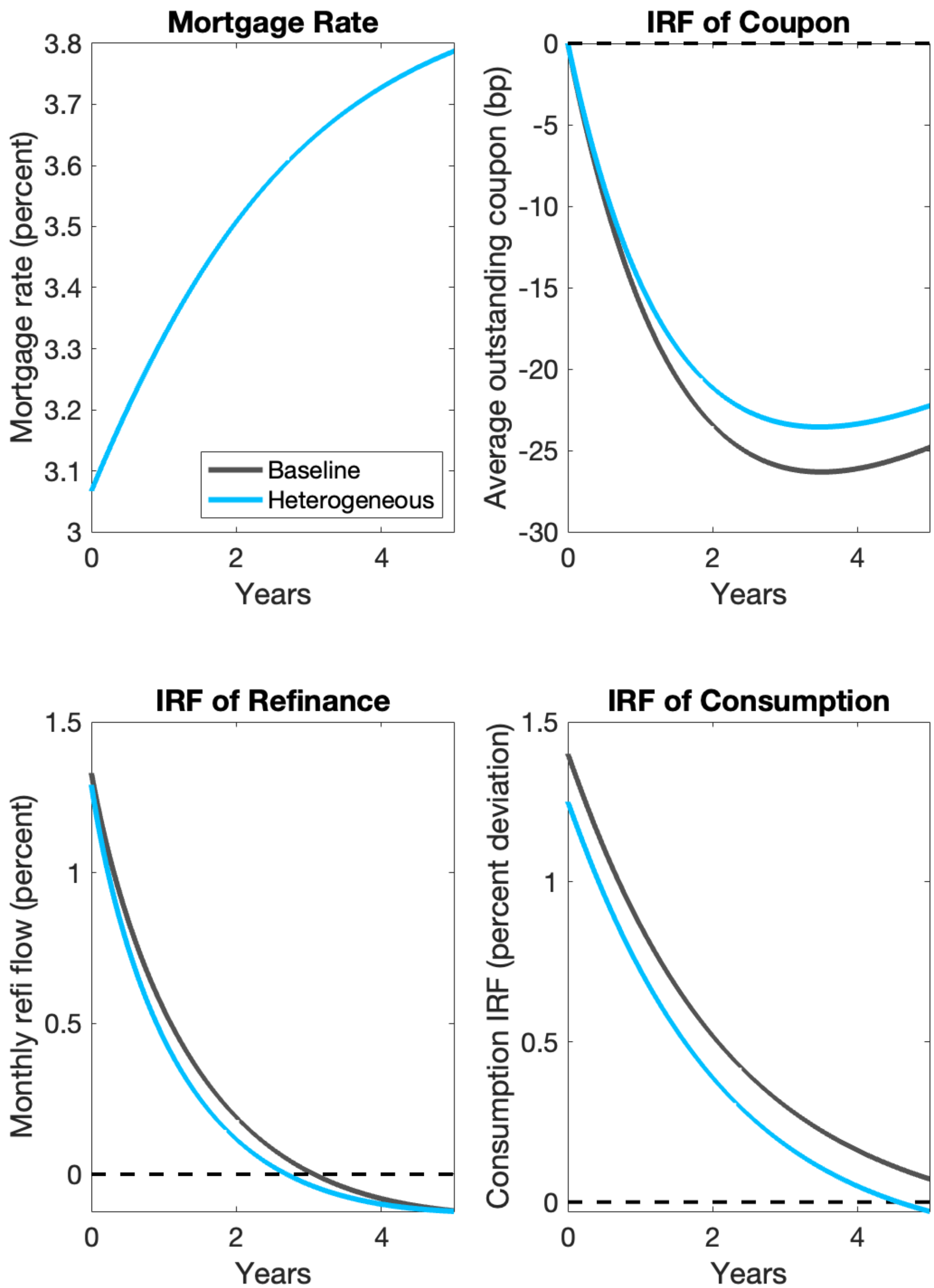
Notes: Figure displays steady state consumption as a function over income, outstanding mortgage rate, and liquid wealth for medium credit score households. See text for details.

Figure 18: Steady State Consumption Function for High Credit Score Households



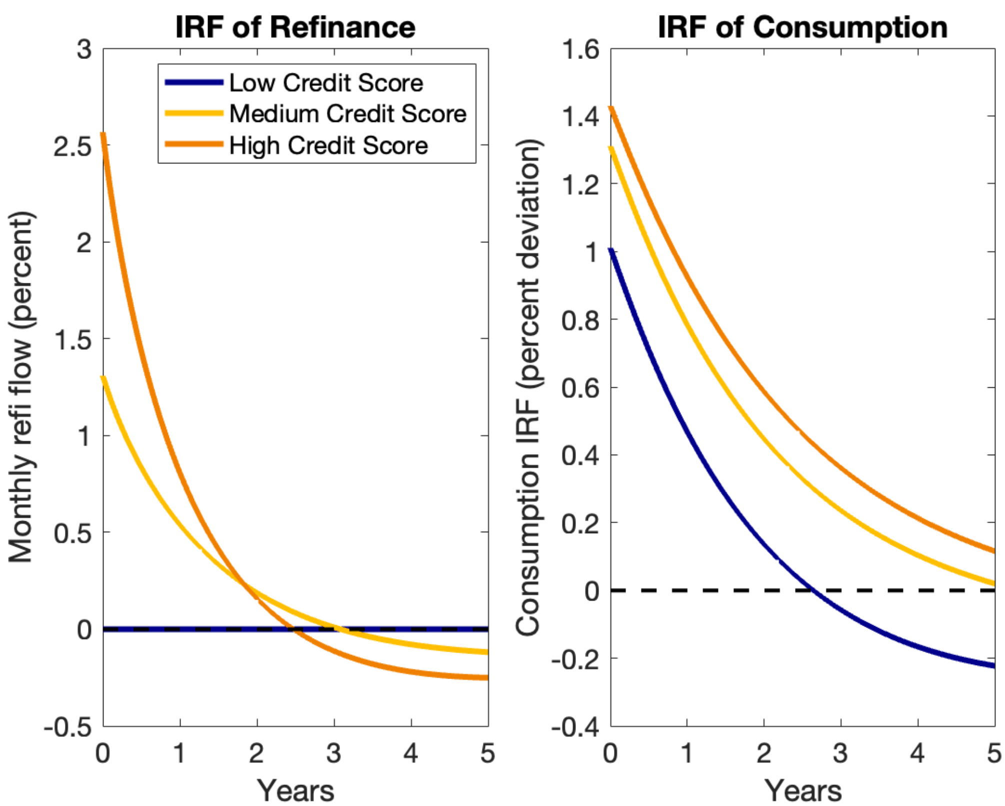
Notes: Figure displays steady state consumption as a function over income, outstanding mortgage rate, and liquid wealth for high credit score households. See text for details.

Figure 19: Refinancing and Consumption Response to Monetary Policy



Notes: Figure displays the IRF of mortgage rate, outstanding coupon, refinancing rate, and consumption C to a 240 basis point decline in short-term interest rate r.

Figure 20: Refinancing and Consumption Response to Monetary Policy in Heterogeneous Economy



Notes: Figure displays the IRF of refinancing rate and consumption C to a 240 basis point decline in short-term interest rate r for each credit score group.

Table 1: 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: 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 the unit of observation in Panel B is loan-month. Refinance Loan, Purchase Loan, Rate Refinance Loan, Cash-out Refinance Loan, and Refinance are dummy variables.

Table 2: 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: Table reports LPM estimates of loan-level regression (1) – the outstanding mortgage rate on a set of mortgage characteristics and market mortgage rate. The estimation is performed at the monthly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset at their origination date. The unit of observation is a loan-origination month.

Table 3: Baseline Refinance with Interaction Results for Regression (3)

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: Table reports LPM estimates of loan-level regression (3) – the likelihood of mortgage refinance on a set of mortgage characteristics. The estimation is performed at the monthly frequency on 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 variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to 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). Standard errors are double clustered by 3-digit ZIP-code and origination year-month.

Table 4: Robustness of Regression (3) to Inclusion of Additional Interactions

	(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: Table reports LPM estimates of loan-level regression (3) with additional interaction terms – the likelihood of mortgage refinance on a set of mortgage characteristics. The estimation is performed at the monthly frequency on 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 variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to 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). Standard errors are double clustered by 3-digit ZIP-code and origination year-month.

Table 5: Refinance with Interaction Results at Quarterly Frequency

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: Table reports LPM estimates of loan-level regression (3) – the likelihood of mortgage refinance on a set of mortgage characteristics. The estimation is performed at the quarterly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-quarter. All variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to 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 quarters since origination (duration). Standard errors are double clustered by 3-digit ZIP-code and origination year-quarter.

Table 6: Refinance with Interaction Results at ZIP-level

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: Table reports LPM estimates of 3-digit ZIP-level regression (3) – the likelihood of mortgage refinance on a set of mortgage characteristics. The estimation is performed at the monthly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a ZIP-month. All variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to percentage changes. Underwriting characteristics include LTV, DTI, remaining balance. Standard errors are double clustered by 3-digit ZIP-code and year-month.

Table 7: Effect of QE1 on Differences in Refinance Probabilities for Regression (**??**)

window	6-month			1-year		
1{Refi}	(1)	(2)	(3)	(4)	(5)	(6)
gap	0.281***	0.538***	0.372***	0.527***	0.704***	0.619***
	(0.027)	(0.057)	(0.051)	(0.045)	(0.059)	(0.058)
CS	0.036***	-0.092***	-0.036***	0.030	-0.069***	-0.038***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)	(0.008)
gap × CS	0.106***	0.099***	0.095***	0.152***	0.140***	0.137***
	(0.015)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)
1{postQE$_1$}	0.567***	0.368***	0.433***	0.106	0.752***	0.813***
	(0.117)	(0.084)	(0.083)	(0.063)	(0.080)	(0.077)
gap × 1{postQE$_1$}	0.682***	0.441***	0.766***	0.382***	0.178	0.341***
	(0.102)	(0.078)	(0.073)	(0.062)	(0.061)	(0.067)
CS × 1{postQE$_1$}	0.066	0.186***	0.078	-0.003	0.115***	0.057
	(0.059)	(0.040)	(0.036)	(0.021)	(0.021)	(0.020)
gap × CS × 1{postQE$_1$}	0.466***	0.366***	0.379***	0.330***	0.231***	0.239***
	(0.051)	(0.039)	(0.037)	(0.024)	(0.026)	(0.025)
LTV		-0.527***	-0.353***		-0.414***	-0.329***
		(0.037)	(0.022)		(0.034)	(0.025)
DTI		-0.023	0.044***		-0.007	0.040***
		(0.007)	(0.006)		(0.005)	(0.004)
rem. balance		0.541***	0.073		0.448***	0.152***
		(0.033)	(0.023)		(0.038)	(0.030)
LTV × 1{postQE$_1$}			-0.288***			-0.130*
			(0.046)			(0.034)
DTI × 1{postQE$_1$}			-0.132***			-0.090***
			(0.018)			(0.013)
rem. bal. × 1{postQE$_1$}			0.847***			0.495***
			(0.054)			(0.057)
# of borrowers		0.184***	0.191***		0.134***	0.141***
		(0.014)	(0.015)		(0.010)	(0.010)
age		0.137***	0.101***		-0.006	-0.019
		(0.021)	(0.019)		(0.007)	(0.008)
age × age		-0.002	-0.001		-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)
constant	0.630***	-2.153***	-2.214***	0.818***	1.545***	1.586***
	(0.013)	(0.344)	(0.302)	(0.021)	(0.136)	(0.137)
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
Observations	7,259,756	6,473,457		14,559,149	12,991,704	
R^2	0.007	0.012	0.013	0.004	0.008	0.009

Standard errors in parentheses
* $p < .00028$, ** $p < .00014$, *** $p < .000028$

Notes: Table reports LPM estimates of loan-level regression (**??**). The estimation is performed at the monthly frequency on 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 variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to 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). Standard errors are double clustered by 3-digit ZIP-code and origination year-month.

Table 8: 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: Table reports first-stage from instrumental variable estimation of loan-level regression (3). In Panel A instruments for 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 gap is the change in 2-year Treasury yield around 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 at the monthly frequency on 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.

Table 9: OLS and IV Results Refinance Probabilities for Regression (3)

1{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: Table reports OLS and IV LPM estimates of loan-level regression (3). See text for details on instruments. The estimation is performed at the monthly frequency on 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 variables, except the rate gap, were standardized around mean. Refinance indicator was multiplied by 100 to arrive to percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a

Table 10: Model Parameter Values

Parameter	Value	Description	Target or Source
		Exogenous Parameters	
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 3.91% in 2019
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	8.65% p.a.	household discount rate	median wealth of \$48,362
			weighted average of wealth (excluding home equity) medians
			for Millennials, Generation X, Baby Boomers
F	\$225,230	mortgage balance	average in data
		Refinance and Borrowing Parameters	
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 low credit score group	assumption
χ_M	26.54% p.a	shock arrival rate for medium credit score group	refinance rate for $gap > 0$, FICO < 75^{th} percentile
χ_H	54.49% p.a	shock arrival rate for high credit score group	χ in baseline economy, given χ_L, χ_M
b	\$30,000	borrowing limit	average credit card limit in 2019
b_L	\$0	assumption	
b_M	\$15,000	assumption	
b_H	\$45,000	b in baseline economy, given b_L, b_M	

Table 11: Steady State Summary Statistics

	Baseline Economy	Heterogeneous Economy			
		Low	Medium	High	Total
Average consumption ($)	63,955	63,550	64,173	64,224	63,982
Average MPC out of wealth	0.33	0.47	0.36	0.27	0.37
Share of constrained households	2.3%	2.5%	2.6%	2.1%	2.4%
Share of households with $W \leq 0$	6.3%	2.5%	4.7%	9.1%	5.4%

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

Table 12: Consumption Response Decomposition

	Baseline Economy	Heterogeneous Economy			
		Low	Medium	High	Total
Wealth effect (bps)	119 (85%)	101 (100%)	110 (84%)	125 (87%)	112 (90%)
Total effect (bps)	140	101	131	143	125

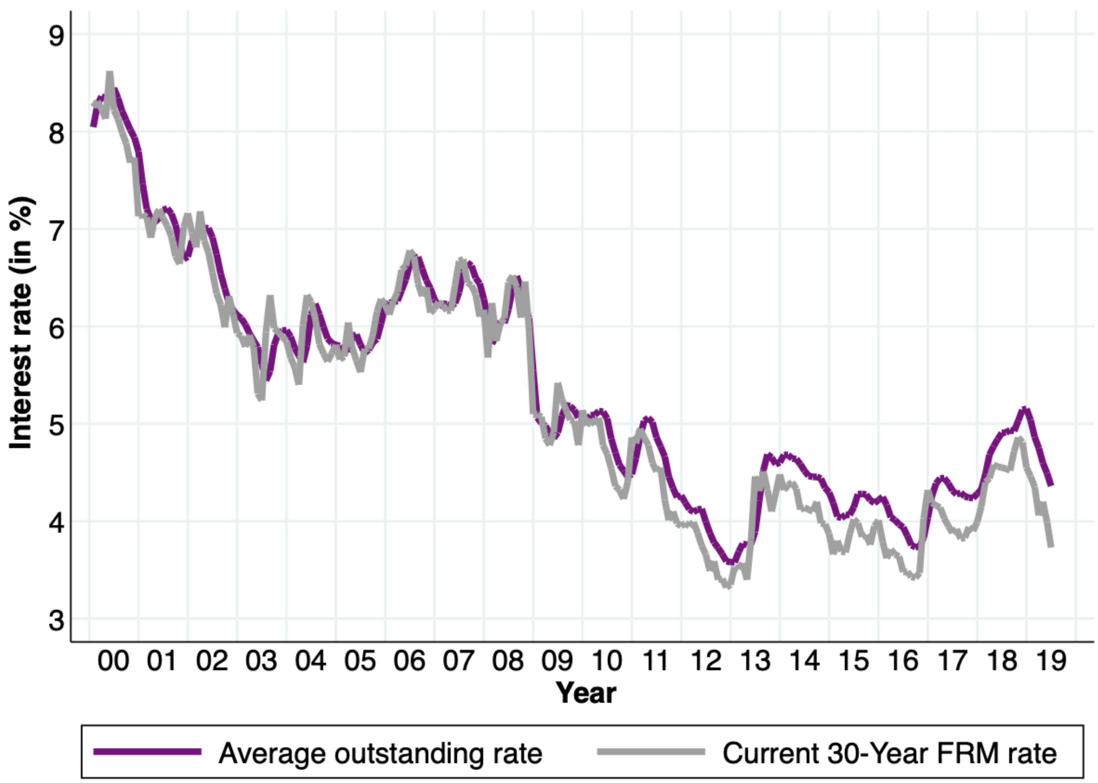
Notes: This table decomposes the channels through with monetary policy produces a consumption response on impact. The first row presents the consumption elasticity when households are not allowed to refinance. The second row presents the consumption response in the full model. Parentheses indicate the share of the total consumption response.

Appendices

A1 Mortgage Sample Representativeness

We treat our sample as representative of the population - Figure A1 shows that the mean mortgage rate for contracts in our sample heels the monthly average of the Freddie Mac weekly PMMS survey 30-year FRM average.

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

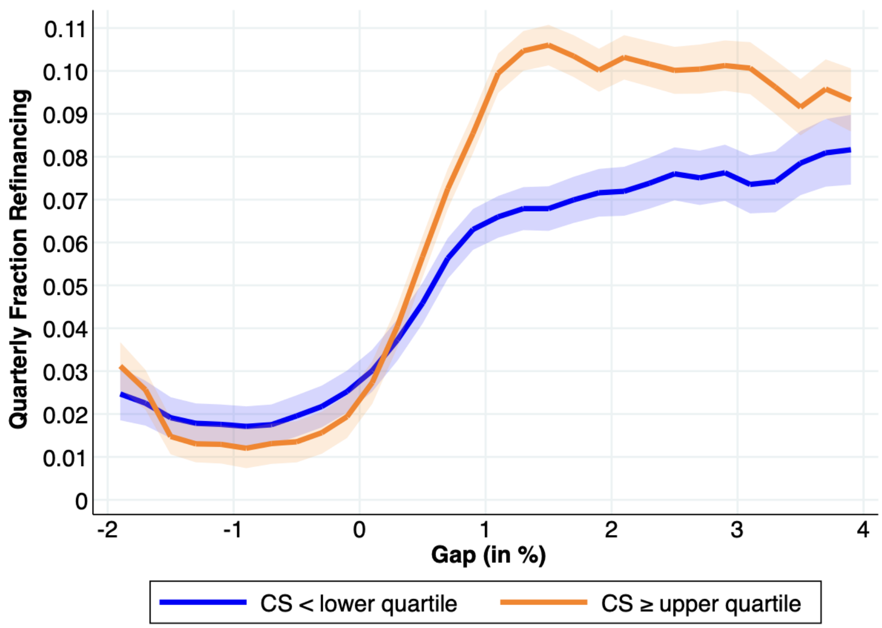


Notes: Figure shows the average outstanding mortgage rate of the Fannie-Mae Single-Family Loan-Level historical data and the market mortgage rate from FRED, Federal Reserve Bank of St. Louis at https://fred.stlouisfed.org/series/MORTGAGE30US.

A2 Additional Empirical Results

Figure A2 is the quarterly version of Figure 11 in the main text. The key difference between Figure 11 is that the interest rate gaps and refinance indicator are averaged quarterly (as opposed to monthly). A comparison between Figure 11 and Figure A2 shows that they are very similar. In particular, both show significant differences in refinance between lower and upper quartile credit score borrowers.

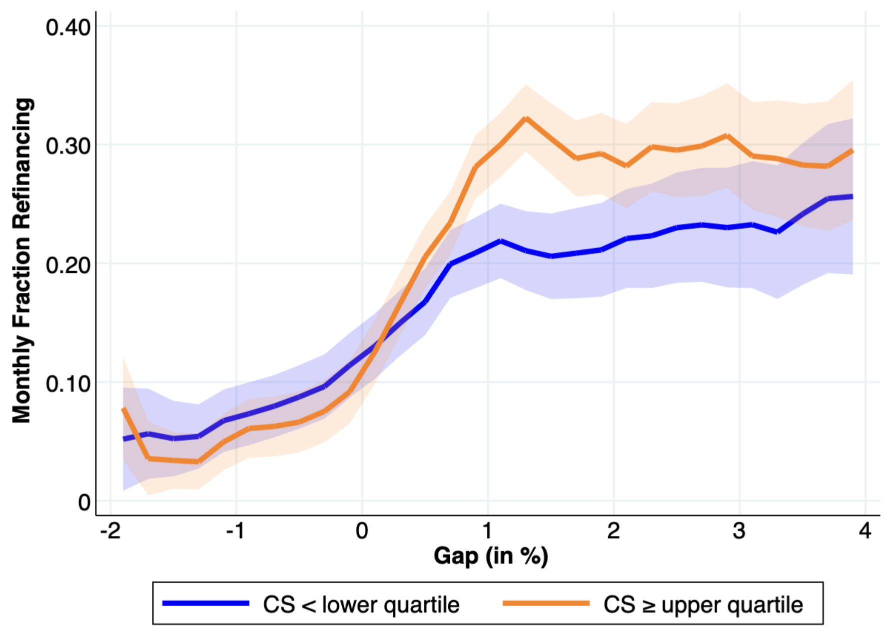
Figure A2: Robustness of Refinance Hazard to Quarterly Frequency for Lower and Upper Quartile Credit Score Borrowers



Notes: Figure shows point estimates for coefficients $\beta+\gamma+\delta$ 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 at the quarterly frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-quarter. 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-quarter.

Figure A3 is the annualized version of Figure 11 in the main text. The key difference between Figure 11 is that the interest rate gaps and refinance indicator are averaged annually (as opposed to monthly). Even annualized refinance hazards for lower and upper quartile credit score borrowers differ significantly for rate gaps below 2%. For higher rate gaps, hazard estimates become increazingly imprecise.

Figure A3: Robustness of Refinance Hazard to Annual Frequency for Lower and Upper Quartile Credit Score Borrowers



Notes: Figure shows point estimates for coefficients $\beta+\gamma+\delta$ 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 at the annual frequency on a 10% random sample of loans from the Fannie-Mae Single-Family Loan-Level historical dataset. The unit of observation is a loan-year. 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.

A3 Differences in Refinancing between Lower and Upper Quartile Credit Score Borrowers

Table A1: Differences in Refinancing between Lower and Upper Quartile Credit Score Borrowers

	$Refi^L - Refi^H$
$r^L - r^H$	1.527***
	(0.407)
constant	-1.149***
	(0.259)
Observations	157
Adjusted R^2	0.112

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A4 Construction of Monetary Policy Shocks

We use high-frequency measures of monetary policy shock. High-frequency identification controls for 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 Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect 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 futures contracts at horizons of 2, 3, and 4 quarters, and 2-, 5-, and 10-year Treasury yields.

We focus only on scheduled FOMC meetings as unscheduled meetings may occur in response to other contemporaneous shocks. The outliers in a few periods can disproportionately affect the estimation of shocks across all dates in the sample. To avoid this problem, we follow Nakamura and Steinsson (2018) and Swanson (2021) who omit the FOMC announcement on September 17, 2001, which took place before markets opened but after financial markets had been closed for several days following the 9/11 terrorist attacks.

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 quote 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 contract expiring in the current month ($ff1_{t-\Delta t}$) is a weighted average of the average Fed Funds rate prior to 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. 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 window is small, we assume that change in risk premium is zero. Same procedure is then applied to changes in fed funds target after the second FOMC meeting from now (r_2). $ff2$ is the fed funds futures rate for 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 $T \times n$[22] 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,

$$X = F\Lambda + v \tag{A1}$$

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

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

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, variance of LSAP factor is minimized in the pre-ZLB period corresponding to sample from January 1, 1999, to February 1, 2009.

We perform two normalization 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 to have 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 easing.[23] 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 A2 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 is largest at the short end of the yield curve and dies off monotonically as the maturity of the interest rate increases. This is in line with the results from Gürkaynak, Sack, and Swanson (2005), and Swanson (2021).

In the second row, the effect of forward guidance is completely different. The zero effect on the current federal funds rate is by construction. But, as we can see in the estimates from the expected federal funds rate onward, the effect of forward guidance has more of a hump shaped response, where it peaks at approximately the one year horizon and then diminishes at longer horizons. This hump shaped response is also consistent

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

	$mp1$	$mp2$	$ed2$	$ed3$	$ed4$	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

$^{*} p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$

Table A2: 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.

with Gürkaynak, Sack, and Swanson (2005), and Swanson (2021).

In the case of LSAPs in the third row, the effect on the current federal funds rate is zero by construction and a one standard deviation increase in LSAP causes the 2-, 5- and 10- year treasury yields to fall on average, consistent with Swanson (2021).

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

A5 Household Problem Solution

The system to be solved is characterized by Hamilton-Jacobi-Bellman equation (HJB) and Kolmogorov Forward equation (KFE). HJB equation corresponding to household value function $V(r, W, m^*, Y)$ is given by

$$\begin{aligned}\delta V(W, r, m^*, Y) = \max_C u(C(W, r, m^*, Y)) + \mathscr{L}_r V + \mathscr{L}_Y V \\ + (\nu + \chi_j 1\{m(r) < m^*\}) \left[V(W, r, m(r), Y) - V(W, r, m^*, Y)\right] \\ + \left(rW + Y - C(W, r, m^*, Y) - m^* F\right) \partial_W V\end{aligned} \tag{A2}$$

where $\mathscr{L}_r$ is the infinitesimal operator associated with the stochastic process r_t, $\mathscr{L}_Y$ is the infinitesimal operator associated with the stochastic process Y_t.

A6 Calibration of Parameters for Short Term Interest Rate Process

The dynamics of the short term interest rate evolve according to the following stochastic differential equation:

$$dr_r = -\kappa(r_t - \mu)dt + \sigma\sqrt{r_t}dZ_t \tag{A3}$$

We follow Cox, Ingersoll and Ross (2005) to estimate parameters of (A3) using the generalized method of moments (GMM). We apply Euler discretization to obtain

$$\begin{aligned} r_{t+1} &= \alpha + \beta r_t + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= \sigma\sqrt{r_t}\sqrt{\Delta t}N(0,1) \end{aligned} \tag{A4}$$

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 (A4) it follows that

$$\begin{aligned} E[\varepsilon_{t+1}] &= 0 \\ E[\varepsilon_{t+1}^2] &= \sigma^2 r_t \end{aligned} \tag{A5}$$

Using (A5) and orthogonality condition, we can derive four moment conditions such that $E[g(\kappa,\mu,\sigma)] = 0$:

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

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 a 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. Our parameter estimates are found by minimizing J with respect to κ, μ, σ.

This model is overidentified - we have four moment conditions and three parameters to estimate. We will estimate GMM in two stages. First, we minimize objective function using identity weighting matrix. We will 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 Newey-West estimator of 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 our estimation we use daily data for 3-month Treasury yields from 1992 to 2007. This yields $T = 4003$ observations. We set $dt = 1/250$ (daily data) and number of lags in spectral density decomposition $k = 12$ (so our estimates are close to MLE).