Essays in Macroeconomics

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Abstract

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My dissertation combines structural macroeconomic models with analyses of macro and micro data and broadly contributes to two research agendas. The first relates to the channels through which monetary policy impacts the economy. The second aims to understand how heterogeneity observed at the micro level affects the economy.

The first two chapters, "Monetary Policy and Heterogeneous Mortgage Refinancing" and "A Model of Heterogeneous Mortgage Refinancing," focus on the refinancing channel of monetary policy. Since fixed-rate mortgages are the most significant source of household debt in the U.S., monetary policy can stimulate household consumption and wealth by lowering mortgage costs through refinancing. The potency of this channel will depend on households' outstanding mortgage rates, as well as their willingness and ability to refinance. I combine empirical patterns from monthly loan-level data (from joint work with A.Burya) and a heterogeneous agent model of mortgage refinancing to show that credit score heterogeneity dampens the aggregate consumption response to monetary policy by 11%.

The third and fourth chapters, "Anchoring of Inflation Expectations: An Empirical Test" and "Anchoring of Inflation Expectations: Role of Risk Premia," study the effectiveness of monetary policy in the U.S. by exploring the degree to which inflation expectations are anchored. If inflation expectations are well-anchored, then the Fed has a higher capacity to support aggregate employment when necessary, without destabilizing inflation. In joint work with A.

Burya and S. Mishra, I construct a proxy of the change in the Fed's aggressiveness to inflation and develop an empirical test for inflation expectations anchoring. The proxy of the changes in the Fed's aggressiveness is equal to changes in expectations of future policy rates that are unexplained by the information contained in the inflation news release. The empirical test involves examining the sensitivity of inflation expectations to monetary policy shocks conditional on that proxy. I then use a measure of inflation expectations adjusted for inflation and liquidity risk premia to demonstrate that bond yield data in the U.S. is consistent with the anchoring of the long-term inflation expectations.

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Finally, I am indebted to my parents, Nino and Georgy, my brother Sandro, and my friends Natasha, Katya, and Francisco, who gave me their love, energy, and inspiration every day.

Dedication

To my mother. For her endless love, patience, and belief in me.

Chapter 1: Monetary Policy and Heterogeneous Mortgage Refinancing

Joint work with A. Burya.

1.1 Introduction

Monetary policy can stimulate household consumption and wealth by lowering mortgage costs through refinancing. In the U.S., 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, 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 can access mortgage markets. This

[1] Goodman et al. (2019) document that in the U.S., mortgages add up to 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 loan outstanding mortgage rate 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 et al. (2020), Gerardi, Willen, and Zhang (2020).

[4] Over the last years, the fraction of denied refinance applications was higher than that 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).

heterogeneity in refinancing opportunities can therefore dampen the effects of monetary policy.

In this chapter, we analyze empirical patterns from monthly loan-level data to show that monetary transmission through the FRM channel is limited because refinancing depends on borrowers' credit score distribution besides their rate gap distribution. Borrowers with lower credit scores are less likely or able to refinance their mortgages. If they also have higher marginal propensities to consume, they would benefit from refinancing more than borrowers with higher credit scores. Consequently, 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, we analyze Fannie Mae Single-Family Loan-Level historical data. We estimate that a 1 percentage point increase in the rate gap increases the refinancing probability for borrowers with a FICO credit score of 800 twice as much as that for borrowers with a FICO score of 700.

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 borrowers in lower and upper quartile credit score distribution, even after controlling for observable loan characteristics and fine geographic-by-time fixed effects. Third, we argue that credit score heterogeneity is more important than that across other loan characteristics, such as debt-to-income (DTI) and loan-to-value (LTV) ratios. Finally, we exploit exogenous changes in monetary policy to measure the marginal effect of credit score heterogeneity on refinancing 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 evidence of time-varying credit score distribution. A credit score is the crucial underwriting criterion that affects 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 gap distribution and demographic characteristics documented in the refinancing literature.

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, credit score bin, and other loan characteristics. Pooling observations across time, we sort borrowers into rate gap bins and credit score quartiles and calculate the fraction of refinanced loans in each rate gap bin and credit score quartile. We then show that refinancing hazards for each credit score quartile exhibit a step-like shape: refinancing rates are low and constant among loans with negative rate gaps, and are high and constant among loans with positive rate gaps. However, among mortgages with positive rate gaps, loans with credit scores in the upper quartile have a much higher probability of refinancing than loans in the lower credit score quartile. The difference in refinancing between lower and higher credit score quartiles is robust to excluding loans with high loan-to-value ratios, observations during 2007 – 2011 when households were more likely to be unemployed, and loans with substantial remaining balances.

The credit score heterogeneity in refinancing is significant and larger than that in other borrower characteristics – LTV, DTI, and remaining balance. They are robust to (i) using an alternative definition of rate gap aiming to remove borrower fixed effects, (ii) controlling for payment history rather than the remaining balance, (iii) aggregation to quarterly frequency and a 3-digit ZIP-code level. This result is driven by episodes of mortgage rate decreases because it is much smaller during cycles of tight monetary policy.

Finally, to quantify the effect of credit score heterogeneity on refinancing, we instrument rate gaps with high-frequency monetary shocks to avoid endogeneity because of confounding factors such as household liquidity constraints during recessions that prevent them from paying refinancing costs. 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 considering rate changes only within a small window. A 1 percentage point increase in the rate gap leads to a 1.25 percentage point increase in the likelihood of refinancing for borrowers with a credit score of 800. However, this likelihood rises by only 0.54 percentage points for borrowers with a credit score of 700. The marginal impact of a standard deviation increase in credit score amounts to 27% of the average monthly refinancing rate.

1.2 Related Literature

Our findings contribute to contemporary mortgage research in two significant ways. First, we extend the existing literature on the mortgage market in monetary policy implementation by quantifying monetary policy transmission to the FRM refinancing using loan-level data. Second, we shed light on a novel source of heterogeneity of monetary policy transmission - a credit score - that inhibits the smooth functioning of this channel.

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 et al. (2017)). The most recent research studies the FRM market because 30-year FRMs are the dominant type of mortgage contract in U.S. housing (see Berger et al. (2021), DiMaggio, Kermani, and Palmer (2020), Martin et al. (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 can divide the literature on the heterogeneity of monetary policy transmission through the mortgage markets into two strands – one that examines demand-side consideration and the other that focuses on supply-side constraints. Our main contribution is to show that credit score heterogeneity is significant and more important for aggregate refinancing than other loan characteristics, such as DTI and LTV ratios, that matter in the refinancing literature.

Many demand-side factors related to the distribution of borrower characteristics matter for aggregate refinancing. For example, Cloyne, Ferreira, and Surico (2020) study how the distribution of renters vs. owners affects aggregate refinancing in the U.S. and the U.K. Andersen et al. (2020) show that refinancing is sub-optimal because of borrower inattention. Gerardi, Willen, and Zhang (2020) and Wong (2021) explore the role of demographic characteristics, such as race and borrower age, respectively. Bhutta and Keys (2016) document differential cash-out refinancing responses to changes in interest rate and house prices fluctuations during the housing boom by credit score and borrower age. Martin et al. (2018) examine the effect of regional house price changes on the ability of households to refinance their mortgages. While we employ a reduced form estimation similar to theirs, we focus only on rate refinancing, including the post-financial crisis period, and ignore refinancing due to house price changes that are indirectly affected by monetary policy.

Another strand of the literature shows that, besides borrower characteristics, sub-optimal borrowing depends on supply-side factors, such as lender constraints. Calza, Monacelli, and Stracca (2013) show how the dominant type of contract (adjustable rate vs. fixed-rate) affects refinancing in different countries. Agarwal et al. (2018) show that even though marginal borrowing probability is higher for the lowest FICO credit score consumers, higher credit card limits resulting from credit expansion policies reduce profits from lending, leading to a decrease in aggregate credit card borrowing. Greenwald (2018) emphasizes the importance of LTV and DTI ratios for aggregate refinancing by studying the theoretical implications of the model with such frictions. In this chapter, we focus only on FRMs, the dominant type of contract in the U.S. We control for DTI and LTV ratios and take care of the effects of changing underwriting criteria by including mortgage origination time fixed effects. We capture slowly moving lender concentration with fine time-by-geographic fixed effects.

Two papers that are closely related to ours are Berger et al. (2021) and Eichenbaum, Rebelo, and Wong (2022). They 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 scenario in which people with the most extensive benefits from refinancing can freely do so.

The structure of the chapter is as follows. In section 1.3, we describe the Fannie Mae Single-Family Loan-Level data used in our empirical analysis. In section 1.4, we document empirical results on credit score heterogeneity. In subsection 1.4.1, we provide visual evidence suggesting that credit score distribution affects refinancing and is a potential source of heterogeneity. In subsection 1.4.2, we document significant differences in refinancing across borrowers in different credit score quartiles by plotting a prepayment hazard as a function of the interest rate gap for different credit score groups. In subsection 1.4.3, we show that credit score heterogeneity is robust to controlling for the observable loan characteristics and fine geographic-by-time fixed effects and provide evidence that credit score heterogeneity is more important than that across other loan characteristics, such as debt-to-income (DTI) and loan-to-value (LTV) ratios. In subsection 1.4.4, 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. We conclude the chapter in section 1.5.

1.3 Data

To show that borrowers with lower credit scores are less likely to refinance in response to expansionary monetary policy, we use Fannie Mae Single-Family 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 et al. (2019)). This mortgage-level panel data contains

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

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 monthly from the 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 during the period of January 2000 to March 2019. The data on loan performance extends through December 2021. 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 we conduct our analysis on the monthly frequency where the unit of observation is a loan-month, we work with a 10 percent random sample of the Fannie Mae Single-Family data set to ease the computational burden. We construct our sample by selecting a 10 percent random sample of loans originated in each quarter during our sample period.[6] The total number of FRMs is 3,580,928, resulting in 149,070,748 loan-month observations. In our analysis, we employ the information on the remaining loan balance in each month from origination to prepayment, outstanding (fixed) interest rate, FICO credit score, DTI, LTV, loan purpose (cash-out refinance, rate refinance, purchase of a new house), and a 3-digit ZIP-code recorded at the mortgage origination.[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 et al. (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 the 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 as the ratio of the loan amount at the time of origination to the LTV at origination. Second, we divide the

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

[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.

remaining loan balance by the value of the mortgaged property at origination.

Table 1.1 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 observation unit is a loan (that is, one observation per loan). Panel B displays summary statistics of the time-varying variables included in our analysis, where the observation unit is a loan-month (that is, multiple observations per loan).

Table 1.1: 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		

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

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

$$m_{it} = \alpha_0 + \alpha_1 CS_{it} + \alpha_2 CS_{it}^2 + \alpha_3 LTV_{it} + \alpha_4 LTV_{it}^2 + \alpha_5 DTI_{it} + \alpha_6 DTI_{it}^2 + \alpha_7 r_t^m + \varepsilon_{it} \tag{1.1}$$

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

Table 1.2 displays estimation results of regression (1.1) and shows that coefficients are consistent with previous findings in the literature. Borrowers with higher credit scores, lower LTV, and lower DTI ratios tend to have lower mortgage rates. This specification explains about 90 percent of the 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 1.1 shows that the average mortgage rate for contracts in our sample (5.08) is close to the market 30-year FRM average (5.25). In Appendix A.1, 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, comparable to 1.5 percent in Berger et al. (2021) for the period from 1992 to 2017.

Figure 1.1 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 the lower quartile.

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

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

Table 1.2: Results for Regression (1.1)

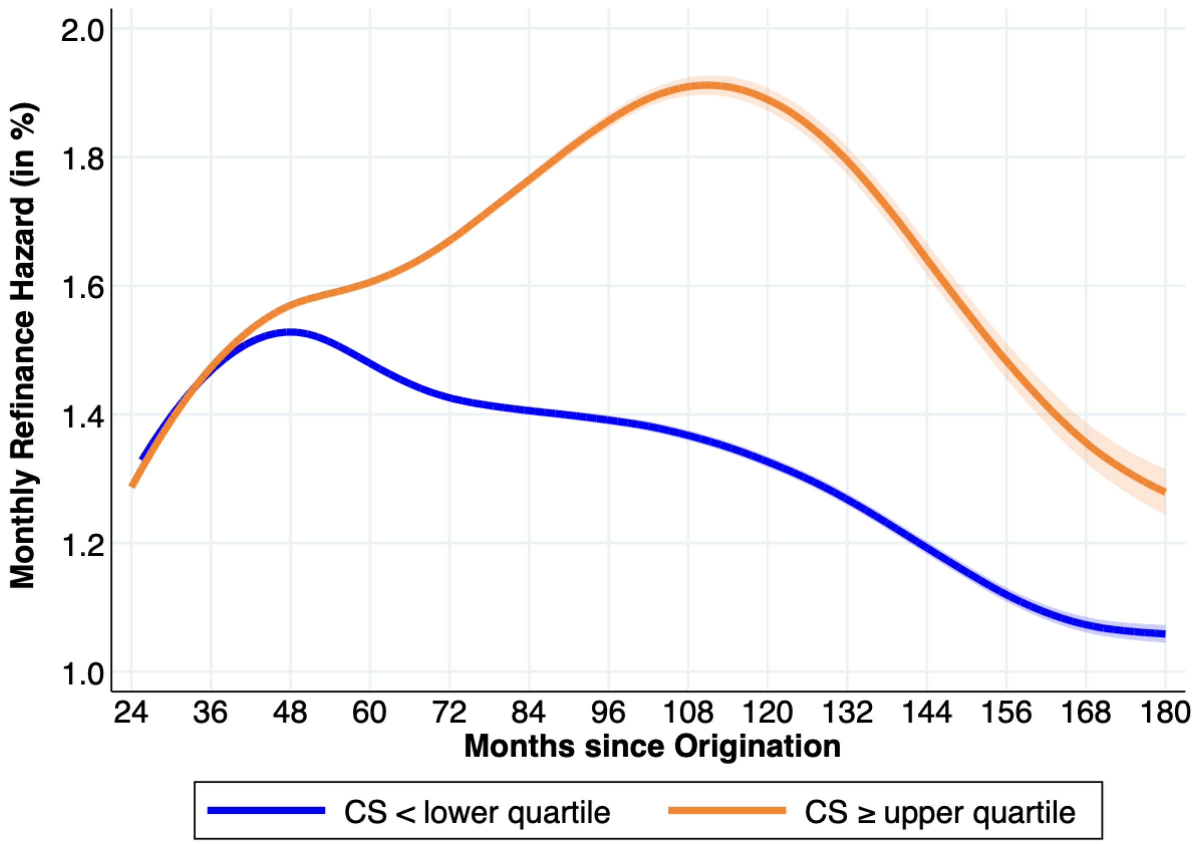
	Outstanding Mortgage Rate
CS	-0.012***
	(0.000)
CS × CS	0.000***
	(0.000)
LTV	0.003***
	(0.000)
LTV × LTV	0.000***
	(0.000)
DTI	0.002***
	(0.000)
DTI × DTI	0.000***
	(0.000)
market mortgage rate	0.910***
	(0.000)
constant	5.593***
	(0.052)
Observations	3,533,488
R^2	0.897

Standard errors in parentheses

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

The table reports LPM estimates of loan-level regression (1.1) – 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.

Figure 1.1: Smoothed Kaplan-Meier Unconditional Refinance Rates



The 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 refinancing 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. The figure uses the Fannie-Mae Single-Family Loan-Level historical dataset.

1.4 Empirical Results

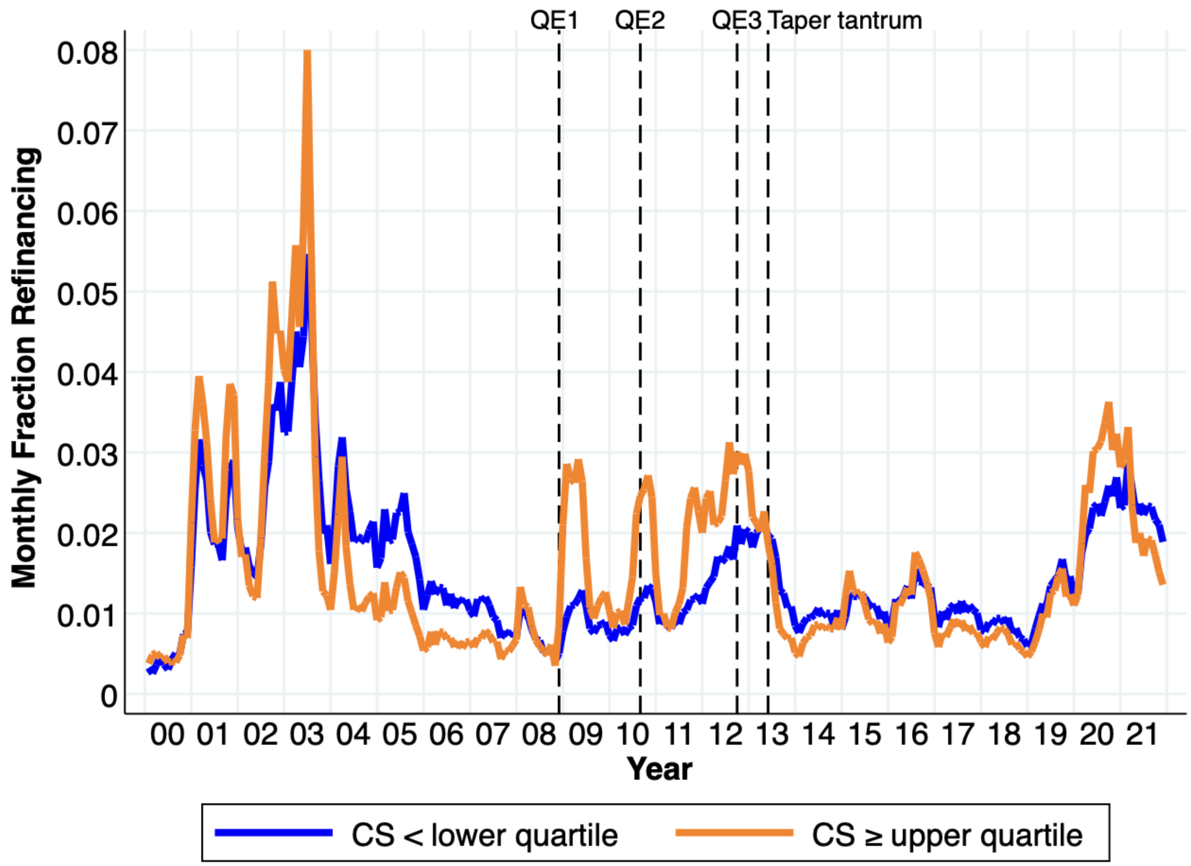
In this section, we show that the refinancing response to monetary policy depends on borrowers' credit score distribution. Our analysis comprises four steps. First, we provide visual evidence suggesting that credit score distribution affects refinancing and is a potential source of heterogeneity. Second, motivated by this observation, we find significant differences in refinancing across borrowers in different credit score quartiles. We start with plotting a prepayment hazard as a function of the interest rate gap for different credit score groups. We then show that credit score heterogeneity is robust to controlling for the observable loan characteristics and fine geographic-by-time fixed effects. Next, we provide evidence that credit score heterogeneity is more important than that across other loan characteristics, such as debt-to-income (DTI) and loan-to-value (LTV) ratios. Finally, we exploit exogenous changes in monetary policy to measure the marginal effect of credit score heterogeneity on refinancing to avoid bias caused by omitted variables that affect both mortgage rate and refinancing through channels distinct from monetary policy.

1.4.1 Credit Score Distribution as a Source of Heterogeneity

We present three pieces of visual evidence suggesting that refinancing depends on credit score distribution. The first shows that the unconditional refinancing rate is higher for borrowers with higher credit scores. The second illustrates rate and credit score dynamics for the borrowers in the same cohort and implies that borrowers with higher credit scores are the ones who refinance most actively. Third, we demonstrate that credit score distribution is time-varying. Time-varying credit score distribution implies that refinancing opportunities are state-dependent (in this case, the state is credit score distribution at each point in time).

In Figure 1.2, we plot the 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 easing QE1 and quantitative easing QE2, the refinancing rate is higher for borrowers with higher credit scores.

Figure 1.2: Unconditional Monthly Refinance Hazard for Lower and Upper Quartile Credit Score Borrowers



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

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 1.3, we plot the average mortgage rate of outstanding contracts that originated in May 2000 and the current market mortgage rate. In the bottom panel of Figure 1.3, we plot the average credit score of outstanding contracts that originated in May 2000. The market mortgage rate declined from 8.5% in 2000 to 3.8% in 2019. If the interest rate is the only determinant of refinancing, we would see the average cohort rate falling over time because borrowers with the highest incentives to refinance would have prepaid their mortgages and left the sample. However, the average rate of outstanding loans in this cohort does not vary much, while their holders' average credit score is dropping, suggesting that borrowers with a higher credit score were more likely to refinance. Single cohort dynamics are similar for other cohorts – in Figure 1.4, we provide the average mortgage rate and average credit score of outstanding contracts originated in May 2009.

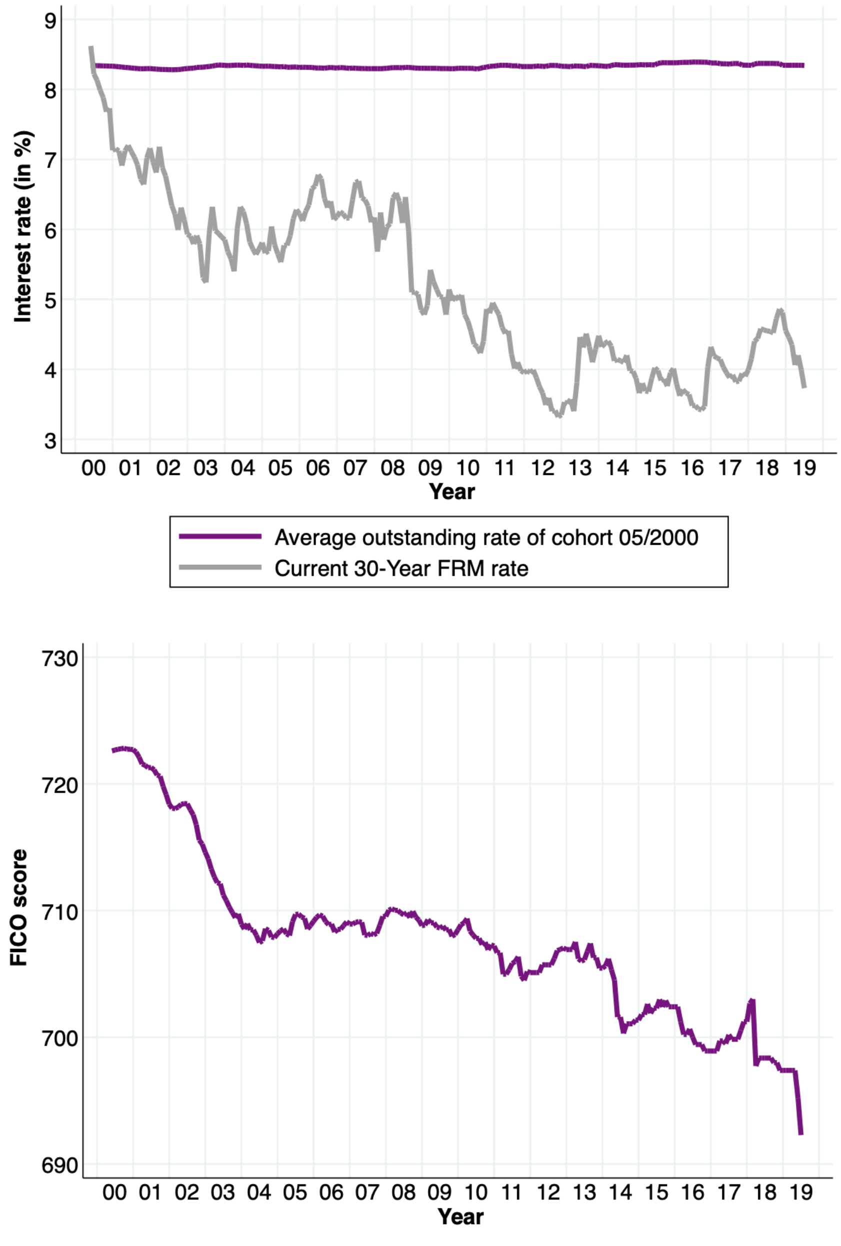
To claim credit score state-dependence, besides the latter observations, one would also need to see the change in the borrowers' credit scores over time. Figure 1.5 suggests that it is indeed the case. Over the last 20 years, the average credit score of new borrowers in the lower quartile has increased by around 40 FICO points, whereas that of the borrowers in the upper quartile by only 20 points. Figure 1.6 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.

1.4.2 Heterogeneous Response of Refinance to Mortgage Rates

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.

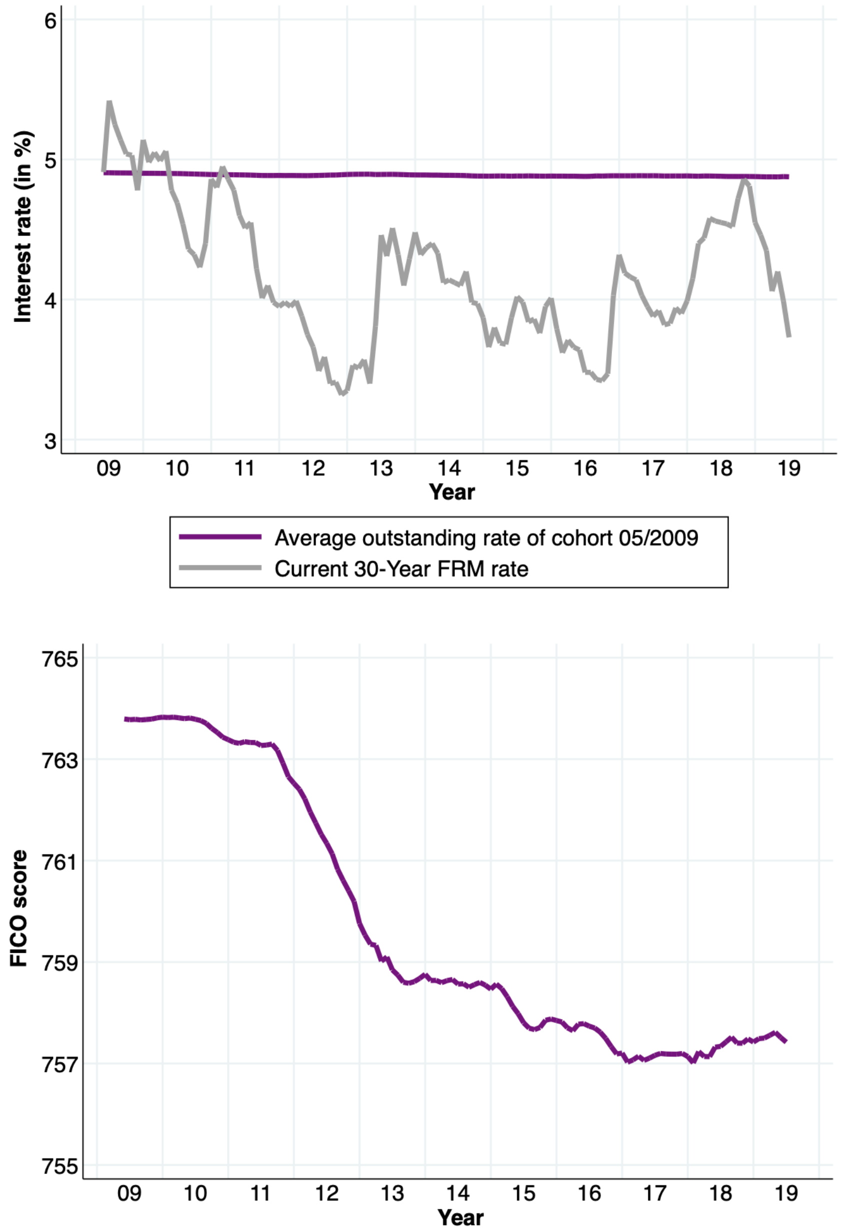
We start by looking at refinancing, pooling all monthly observations for contracts that originated in 2000–2019. We then sort loan-months to 20 basis point wide gap bins and four credit score groups corresponding to quartiles of credit score distribution and estimate a non-parametric rela-

Figure 1.3: Outstanding and Current Market Mortgage Rates (top panel) and Average Credit Score of Outstanding Mortgages (bottom panel) on Mortgages Originated in 05/2000



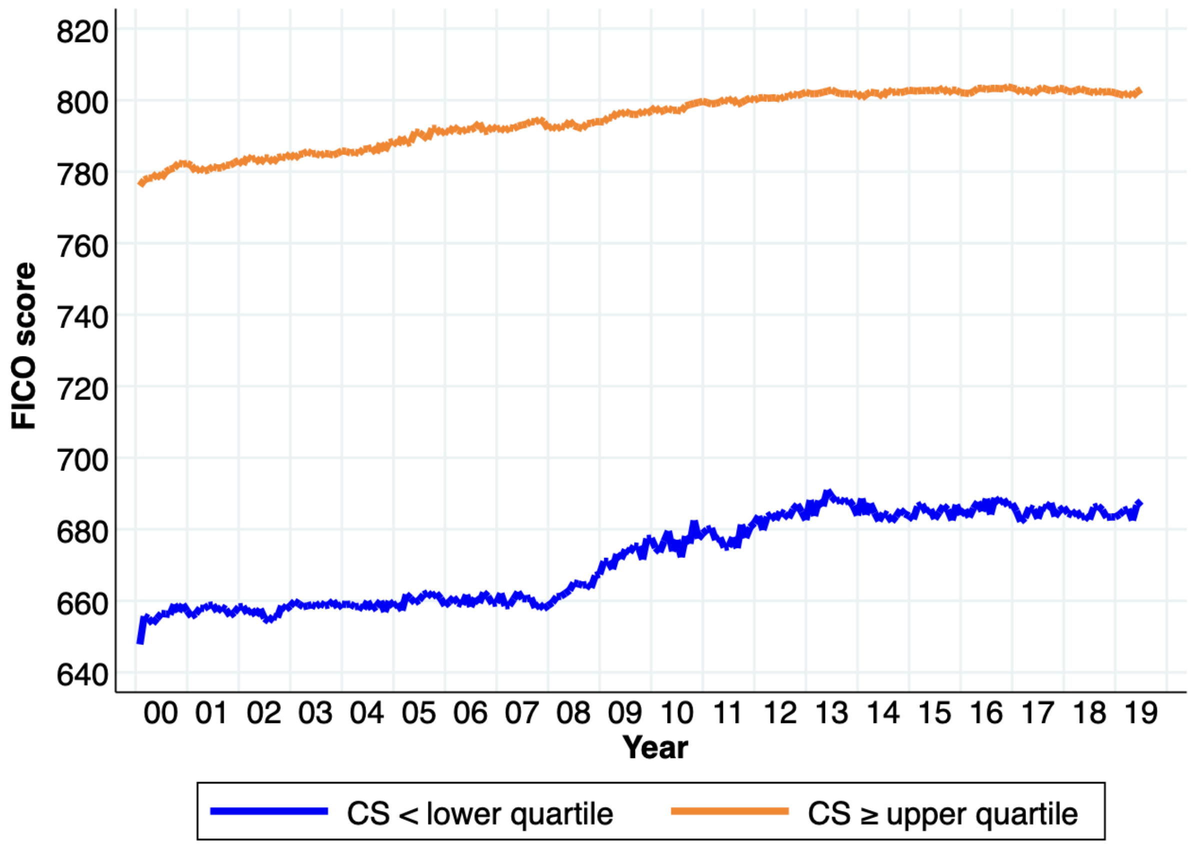
The figure shows the average outstanding mortgage rate along with market mortgage rate (top panel) and average credit score (bottom panel) on mortgages originated in May 2000. Data on the average mortgage rate and average credit score on mortgages originated in May 2000 come from the Fannie-Mae Single-Family 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 1.4: Outstanding and Current Market Mortgage Rates (top panel) and Average Credit Score of Outstanding Mortgages (bottom panel) on Mortgages Originated in 05/2009



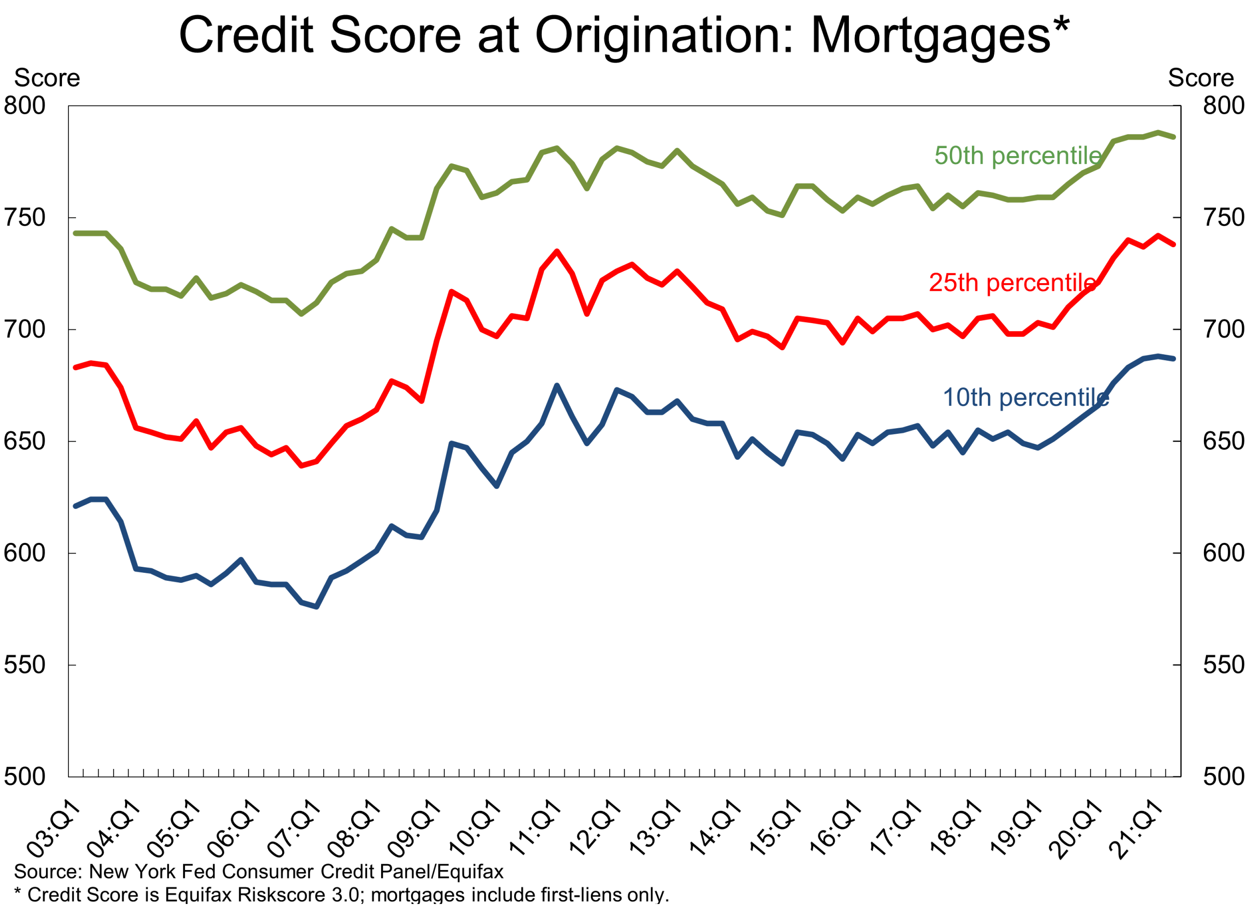
The figure shows the average outstanding mortgage rate along with the market mortgage rate (top panel) and average credit score (bottom panel) on mortgages originated in May 2009. Data on the average mortgage rate and average credit score on mortgages originated in May 2009 and comes from the Fannie-Mae 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 1.5: Credit Score at Origination for Lower and Upper Quartile Credit Score Borrowers



The 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 1.6: Distribution of Credit Score at Origination from New York Fed Consumer Credit Panel/Equifax



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

tionship between refinancing and rate gaps, credit score, and their interaction using the following regression:

$$\mathbb{1}\{\text{Refi}_{it}\} = \alpha + \beta_b \mathbb{1}\{gap_{it}^{bin}\} + \gamma_b \mathbb{1}\{CS_i^{bin}\} + \delta_b \mathbb{1}\{gap_{it}^{bin}\} \times \mathbb{1}\{CS_i^{bin}\} + X_{it}\Gamma + \eta_{ZIP} + \varepsilon_{it} \quad (1.2)$$

where $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy for the gap bin of loan i in month t; $\mathbb{1}\{CS_i^{bin}\}$ is a dummy for the quartile bin of loan i in month t; X_{it} is a vector of loan characteristics which includes a quadratic in LTV, a quadratic in DTI, a quadratic in loan age, and dummy for whether the current loan was itself a new purchase, a cash-out 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.

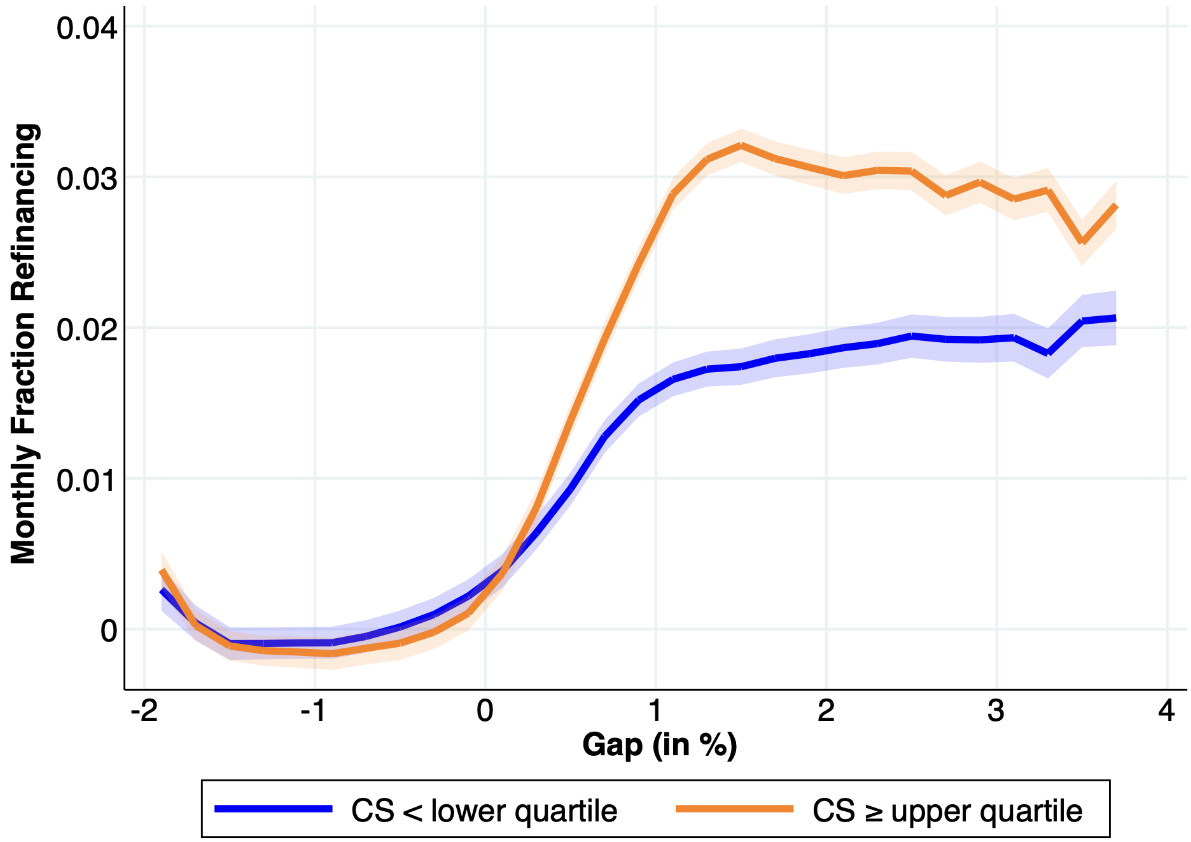
Figure 1.7 shows the resulting monthly refinancing hazard given by the point estimates for coefficients $\beta + \gamma$ for borrowers with credit scores in lower (blue line) and upper (orange line) quartiles with their 95% confidence bands. Two observations stand out. First, there is a positive relationship 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 1.8 shows that restricting our sample to households with an 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 1.9 suggests that our result is robust to restricting our sample to mortgages with an outstanding balance above $100,000 (mean of our sample). In Appendix A.2, 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

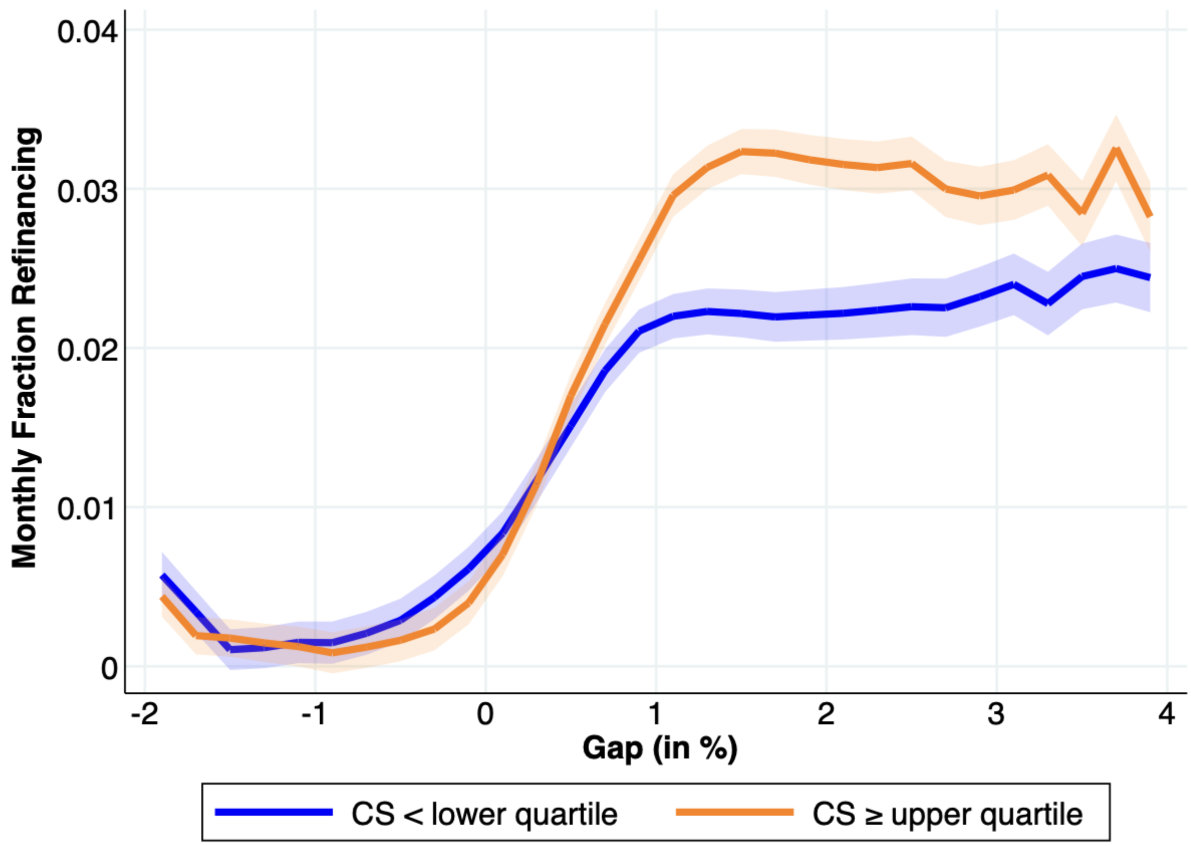
[11] Our results are in line with Berger et al. (2021).

Figure 1.7: Refinance Hazard with Individual Controls for Lower and Upper Quartile Credit Score Borrowers



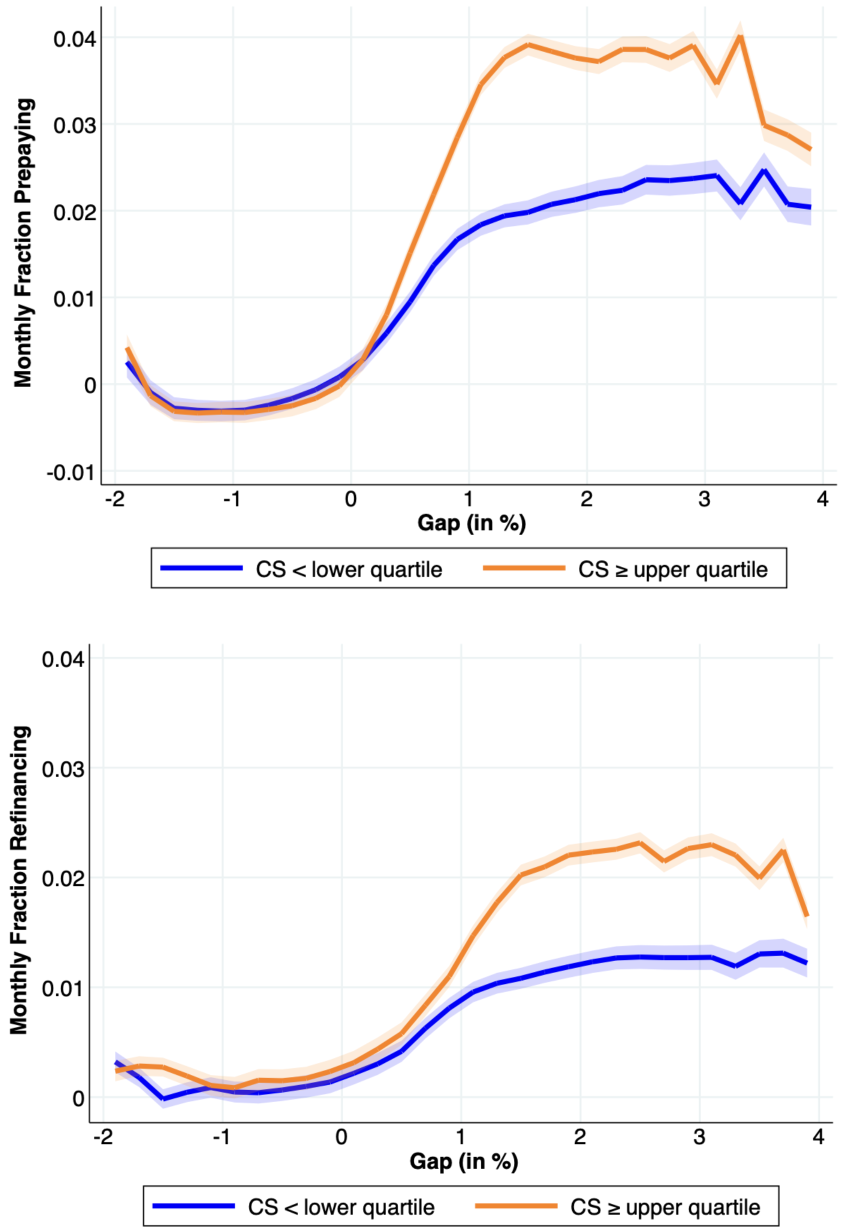
The figure shows point estimates for coefficients $\beta + \delta$ on the 20bp bin dummies in regression (1.2) for borrowers in the lower credit score quartile (blue) and in the upper credit score quartile (orange). The estimation is performed at the monthly frequency on a 10% random sample of loans 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 1.8: Refinance Hazard with Individual Controls: Low LTV Households



The figure shows point estimates for coefficients $\beta + \delta$ on the 20bp bin dummies in regression (1.2) 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 1.9: Refinance Hazard with Individual Controls for Mortgages with Mortgage Balances > \$100,000 (top panel) and Mortgages with Mortgage Balances < \$100,000 (bottom panel)



The figure shows point estimates for coefficients $\beta+\delta$ on the 20bp bin dummies in regression (1.2) 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.

score quartile borrowers with positive rate gaps are significantly large and robust to the inclusion of other borrower characteristics, geographical fixed effects, loan duration, and restricting the sample to loans with the substantial remaining balance.

1.4.3 Robustness

In this subsection, we show that the credit score heterogeneity in refinancing is significant and larger than that in other borrower characteristics – LTV, DTI, and remaining balance. We additionally demonstrate that it is robust to (i) using an alternative definition of rate gap aiming to remove borrower fixed effects, (ii) controlling for payment history rather than the remaining balance, and (iii) aggregation with respect to time and geographical unit. Finally, we show that this result is driven by the episodes of mortgage rate decreases.

To establish that the credit score is the most important source of refinancing heterogeneity, we employ linear probability models and estimate them at a monthly frequency. Our regressions take the following form: for the loan i at month t, we estimate

$$\mathbb{1}\{\text{Refi}_{it}\} = \alpha + \beta gap_{it} + \gamma CS_i + \delta gap_{it} \times CS_i + X_{it}\Gamma + \varepsilon_{it} \tag{1.3}$$

where $\mathbb{1}\{\text{Refi}_{it}\}$ is a dummy variable equal to one if the loan was refinanced; gap_{it} is a rate gap of household i in month t; CS_i is a credit score of household i; $CS_i \times gap_{it}$ is the interaction between credit score and rate gap of household i in month t; X_{it} denotes a vector of controls. 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 the interest rate gap are normalized around corresponding sample means. All coefficients were multiplied by 100 to arrive at 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.

We begin by quantifying credit score differences in the sensitivity of refinancing to gaps δ by running the OLS specification of equation (1.3). The estimation results are provided in Table 1.3.[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 the rate gap and credit score are in line with previous findings of the literature on the 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 the 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 the coefficient before the interaction term should be positive. This is confirmed in column (2) of Table 1.3, which shows that higher credit score borrowers are significantly more likely to refinance in response to the 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 a credit score of 800 (one standard deviation above mean credit score) but only a 0.64 percentage points increase for borrowers with a credit score of 700 (one standard deviation below mean credit score).

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 1.3 we

[12] Note that the 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 the significance level according to the formula $\alpha_{stan} = \alpha/\sqrt{N/100}$.

Table 1.3: Baseline Refinance with Interaction Results for Regression (1.3)

$\mathbb{1}\{\text{Refi}\}$	(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

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

The table reports LPM estimates of loan-level regression (1.3) – 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-month.

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

In column (4) of Table 1.3 we estimate differential sensitivities to the 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 1.3 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 a month.[13] This eliminates concerns that results might be driven by the endogenous monetary policy since the monetary policy does not vary across regions. Moreover, the year-month-by-ZIP-code fixed effects guarantee that identification comes from ZIP-code-specific monthly variation within a 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 the 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 the inclusion of all observable characteristics and time-by-location fixed effects decreases sensitivities to the rate gap between lower and higher credit score borrowers only by 9% in absolute magnitude, from 0.27 to

[13]For example, controls for the year 2003 will take care of a large spike in refinancing in 2003 documented by Alejandro, E., and Andrea (2022).

0.24.

Other Sources of Heterogeneity

In this subsection, we test whether there is the heterogeneity of refinance to rate gap across other borrower characteristics by including additional interactions to our main specifications. It might be the case that these factors that affect refinancing also vary with rate gaps similarly to credit scores. 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.

Column (1) of Table 1.4 corresponds to the specification in column (5) in Table 1.3, 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 1.4 we add the interaction of the rate gap with the 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 the unintuitive sign is that borrowers with higher LTV ratios and large rate gaps are also the ones with higher remaining balances. This specification omits the interaction of the gap with the remaining balance and leads to an upward bias of the coefficient.

In column (3) of Table 1.4 we add the interaction of the rate gap with the DTI ratio. Its sign is negative but small in magnitude suggesting that borrowers with a DTI ratio of 45% (one standard deviation above mean DTI) are 0.04 percentage points less likely to refinance than borrowers with a DTI ratio of 35% (one standard deviation below mean DTI).

In column (4) of Table 1.4 we add interaction of the rate gap with the remaining balance. Interestingly, the interaction of the gap with LTV becomes insignificant (and negative). Loans with higher remaining balances are both more likely to refinance and more responsive to interest rates – the interaction between the gap and remaining balance essentially captures savings from refinancing. This finding is consistent with the mechanism proposed in Wong (2021).

Overall, results from Table 1.4 suggest that the inclusion of these additional interactions has not affected the significance of the credit score interaction and only slightly changed its magnitude,

Table 1.4: Robustness of Regression (1.3) 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
* $p < .000083$, ** $p < .000042$, *** $p < .0000083$

The table reports LPM estimates of loan-level regression (1.3) 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-month.

from 0.24 to 0.21. We conclude that credit score heterogeneity has economically significant effects on refinancing.

Alternative Measure of Rate Gap

Since we cannot track the same borrowers over time, we construct an alternative measure of the rate gap that has a lower measurement error due to the borrower fixed effects. In this subsection, we show that our main result is robust to using this measure.

We construct rate gap, $gap_{it} = \hat{m}_{i\tau} - \hat{m}_{it}$, by calculating the difference between the predicted fixed interest rate on the outstanding loan, $\hat{m}_{i\tau}$, and the predicted rate, $\hat{m}_{it}$, for a new FRM originated in period t given borrower/loan characteristics for FICO, LTV, and DTI. Both rates are predictions from the regression (1.1), and $\hat{m}_{i\tau}$ is a prediction for a rate at the time of origination. The rationale behind this definition is to eliminate borrower fixed effects: for example, it could be the case that some borrowers get unusually high or low interest rates for reasons unrelated to underwriting criteria.

The estimation results are provided in Table 1.5. Column (1) reports estimates from a specification without an interaction term, which includes a third-order polynomial for mortgage age (duration) and origination year-month fixed effects which take care of changes in underwriting criteria over time. The coefficients in front of the rate gap and credit score are higher than those reported for the baseline model in Table 1.3. A 1 percentage point increase in this definition of rate gap is associated, on average, with a 1.26 percentage points higher probability to refinance. Borrowers with a 1 standard deviation above mean credit scores are 0.12 percentage points more likely to refinance.

Column (2) of Table 1.5 shows that a 1 percentage point increase in rate gap is associated with a 1.6 percentage points increase in the probability to refinance for borrowers with credit score 800 but only a 1 percentage point increase for borrowers with credit score 700. Column (3) of Table 1.5 includes underwriting characteristics and 3-digit ZIP fixed effects. While the credit score sensitivity to the rate gap is higher than one from Table 1.3 (0.297 vs. 0.238), the relative difference

Table 1.5: Robustness of Regression (1.3) to Using Alternative Measure of Rate Gap

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

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

The table reports LPM estimates of loan-level regression (1.3) 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-month.

between borrowers with excellent and good credit scores is smaller because this measure of rate gap has a larger effect on refinancing. A 1 percentage point increase in the rate gap is associated with a 1.74 percentage points increase in the probability to refinance for borrowers with a credit score of 800 and a 1.15 percentage point increase for borrowers with a credit score of 700.

Payment History

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

The estimation results are provided in Table 1.6. Column (1) suggests that a 1 percentage point increase in rate gap is associated with a 0.88 percentage points increase in the probability to refinance for borrowers with a credit score of 800 and a 0.43 percentage point increase for borrowers with a credit score of 700. The inclusion of other interaction terms in column (2) does not significantly alter the results. Overall, the results from this estimation suggest the same relative difference between excellent and good credit score borrowers.

Time- and Geographical Aggregation

The micro-level evidence thus far shows a strong relationship between rate gaps, credit score sensitivity to rate gap,s 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 1.7 is the quarterly version of Table 1.3. The key difference between the two is that the interest rate gaps, LTV, remaining balance, and refinance indicator are averaged quarterly (as opposed to monthly) for each borrower in our sample. All specifications include age control – third

Table 1.6: Robustness of Regression (1.3) to Inclusion of Payment History

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

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

The table reports LPM estimates of loan-level regression (1.3) 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-month.

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 a credit score of 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. The addition of a full set of year-quarter-by-ZIP-code fixed effects in column (3) only slightly decreases credit score sensitivity to the rate gap, from 0.49 to 0.44 in absolute magnitude.

In Table 1.8 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 a loan-level variation. The specification with a full set of controls in column (3) implies that the credit score sensitivity to the rate gap is 0.20, which is close to its loan-level counterpart of 0.24 from column (5) of Table 1.3.

Tightening Monetary Policy

Market mortgage rates have been mostly decreasing over the last 20 years. To show that expansionary and tightening monetary policy have asymmetric effects, in this subsection, we re-estimate equation (1.3) during two episodes of tight monetary policy – from July 2004 to June 2006 and from December 2015 to December 2018.

Table 1.9 provides estimation results for two episodes of tightening monetary policy. Column (1) implies that credit score heterogeneity did not matter from July 2004 to June 2006. This result is consistent with Amromin, Bhutta, and Keys (2020) who document that borrowers with lower credit scores were more likely to refinance their mortgage to extract cash against increasing house equity caused by rising house prices.

Table 1.7: Refinance with Interaction Results at Quarterly Frequency

$\mathbb{1}\{\text{Refi}\}$	(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

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

The table reports LPM estimates of loan-level regression (1.3) – 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of quarters since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-quarter.

Table 1.8: Refinance with Interaction Results at ZIP-level

$\mathbb{1}\{\text{Refi}\}$	(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

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

The table reports LPM estimates of 3-digit ZIP-level regression (1.3) – 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, and remaining balance. Standard errors are double clustered by 3-digit ZIP code and year-month.

Table 1.9: Refinance During Tight Monetary Policy

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

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

The table reports LPM estimates of loan-level regression (1.3) – the likelihood of mortgage refinance on a set of mortgage characteristics during tightening cycles of monetary policy. 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). All columns include age controls – 3rd order polynomial for the number of months since origination (duration). Standard errors are double clustered by 3-digit ZIP code and origination year-month.

Column (2) of Table 1.9 suggests that credit score heterogeneity was significant during December 2015 – December 2018 tightening cycle. Both rate gap and credit score sensitivity to the rate gap are lower than for the whole sample period. A 1 percentage point increase is associated with a 0.41 percentage point increase in refinancing probability for the borrower with a mean FICO score of 750. The marginal effect of increasing credit score by one standard deviation is 0.08 percentage points.

1.4.4 Causal Effect of Rate Gaps on Refinancing

Our finding that the refinance response to mortgage rates is heterogeneous across borrowers with different credit scores has important implications for monetary policy. Expansionary monetary policy increases rate gaps. Given that the relationship between rate gaps and refinancing is causal, the resulting increase in refinancing will be much higher among higher credit score borrowers than lower credit score borrowers. While the results in the previous 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 an instrumental variable approach to estimate the effects of monetary policy on refinancing probability.

We re-estimate the equation (1.3) using a monetary policy shock as an instrument for the interest rate gap and the interaction of the shock with a credit score as an instrument for the interaction of the rate gap with a credit score. This approach exploits exogenous variation of rate gaps and leaves out variation due to unobserved confounding factors.

Using a high-frequency identification approach, we construct two measures of monetary policy shocks, which are based on Federal funds futures rates, Eurodollar futures rates, and Treasury yields. High-frequency identification controls for market expectations by considering changes in the target rate within a small window and, thus, overcomes two empirical challenges in identifying the effect of monetary policy. The first is that movements in the target rate exhibit both the independent effects of monetary policy and shifts in demand for risk-free assets because the Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect 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 an easing.[14] Each factor is normalized to have a unit standard deviation. For all the details on

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

high-frequency shock construction see Appendix A.3.

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 1.10 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 under-identification based on the Kleibergen-Paap rk LM statistic for robust errors. We also reject the null of weak instruments based on the Kleibergen-Paap Wald rk F statistic.

Point estimates in Panel A of Table 1.10 suggest that forward guidance and LSAP factors have larger effects on the mortgage rate as compared to the 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 Table 1.10 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 1.11 displays the results from estimating equation (1.3) 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 (1), (3), and (5). Both instrumental

[15]Coefficients in Panel A of Table 1.10 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 is 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 the effects of a 1 percentage point change in the current federal funds rate target, one needs to multiply the coefficient by 100bp/8.39bp $\approx$11.92. To compute the effects of a 1 percentage point change in the expected federal funds rate one year ahead, one needs to multiply the coefficient by 100bp/5.68bp $\approx$17.61.

Table 1.10: 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
* $p < .00011$, ** $p < .000056$, *** $p < .000011$

The table reports the first-stage from the instrumental variable estimation of loan-level regression (1.3). In Panel A instruments for the 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 the credit score. Coefficients are in basis points per standard deviation change in the policy instrument. In Panel B the instrument for the gap is the change in the 2-year Treasury yield around the FOMC announcement, and the instrument for gap×CS is the corresponding interaction of shock with the 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.

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 a downward bias. The estimate of sensitivity to the rate gap changes from 0.21 to 0.39 when using the 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 the 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 the 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 the increase in the 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 the mean, the share of refinanced loans rises 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 a credit score of 800 (one standard deviation above mean credit score) but only 0.72 percentage points for borrowers with a credit score of 700 (one standard deviation

[16]The average refinancing rate for the sample of FOMC months is slightly lower compared to the whole sample of 1.53% from Table 1.1.

[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.

Table 1.11: OLS and IV Results Refinance Probabilities for Regression (1.3)

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

Standard errors in parentheses

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

The table reports OLS and IV LPM estimates of loan-level regression (1.3). 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 the mean. Refinance indicator was multiplied by 100 to arrive at percentage changes. Underwriting characteristics include LTV, DTI, remaining balance, number of borrowers, indicators for whether the current loan was itself a new purchase loan, a cash-out refinancing or a rate refinancing, indicator for property type (condominium, co-operative, planned urban development, manufactured home, or single-family home), and occupancy status (principal, second, investor, unknown). Standard errors are double clustered by 3-digit ZIP code and origination year-quarter.

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.

1.5 Conclusion

Using Fannie Mae Single-Family Loan-Level historical data, we have shown that the FRM refinancing response to monetary policy is heterogeneous across borrowers' credit scores. In particular, a 1% expansionary monetary policy shock causes a 1.09pp average increase in the probability to refinance, with one standard deviation increase in the credit score corresponding to a 0.37pp rise in the refinancing probability. 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 monetary policy efficiency.

Chapter 2: A Model of Heterogeneous Mortgage Refinancing

2.1 Introduction

In this chapter, I combine empirical patterns from the Fannie Mae Single-Family Loan-Level historical dataset documented in the previous chapter with a heterogeneous agent model to show that monetary transmission through the FRM channel is limited because it depends on borrowers' credit score distribution besides their rate gap distribution.

Refinancing heterogeneity in any characteristic will affect aggregate spending only if that characteristic correlates with MPC. The data linking refinancing, borrower characteristics, and spending are limited, making it challenging to estimate the correlation between significant determinants of refinancing and spending. However, borrowers' credit scores, among their other characteristics, directly relate to their borrowing constraints. The credit score is a crucial and prohibitive criterion for credit approval. Even if the borrower has access to liquid assets but does not have a sufficiently high credit score, the lender will not originate a loan.

To show that credit score heterogeneity matters for monetary transmission to aggregate consumption, I build a heterogeneous agent model with FRMs similar to Berger et al. (2021). The main experiment is to compare aggregate consumption response to rate cuts in two economies – one where agents have the same access to credit markets and one where agents differ in their credit scores which determines their ability to refinance and borrow.

My refinancing model suggests that credit score heterogeneity is economically significant – the aggregate consumption response to monetary policy on impact is approximately 11% lower than in a standard model with only mortgage rate heterogeneity. The intuition behind this mechanism is: borrowers with lower credit scores have higher marginal propensities to consume (MPCs). They, therefore, benefit from refinancing more than borrowers with higher credit scores, but are less likely or able to refinance their mortgages and borrow unsecured debt. Consequently, 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 and borrow.

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

The novel feature of my model is how it integrates credit score heterogeneity in the heterogeneous economy: credit score determines the ability to borrow in all credit markets. Intuitively, credit score predicts how likely the borrowers will pay a loan back. If this probability is low, they can neither refinance the mortgage nor borrow more unsecured debt.

In the economy where agents (exogenously) differ in credit scores, lower credit score borrowers end up exhibiting higher MPCs than higher credit score borrowers because credit score determines borrowing in two ways. First, borrowers with higher credit scores have a higher probability of receiving the refinancing shock. This assumption is consistent with the main empirical finding from the previous chapter and incorporates demand- and supply-side mechanisms behind credit score heterogeneity. For example, higher credit score borrowers might be more attentive to changes in interest rates. Or banks might transmit lower rates only to higher credit score borrowers. Second, higher credit score borrowers have higher borrowing limits on liquid debt.

I demonstrate that the aggregate consumption response to a 1 percentage point decrease in the market mortgage rate is 11% lower in the economy with credit score heterogeneity compared to the economy without credit score heterogeneity. Monetary policy in this economy affects household consumption through two channels. First is the wealth effect: the cut in interest rate decreases the return on wealth for all agents and makes short-term borrowing cheaper for higher credit score borrowers. Second, the interest rate cut provides higher credit score households with the refinancing option, allowing them to reset their mortgage rate to a lower one, which frees up disposable income for more consumption. Since higher credit score borrowers have lower MPCs than borrowers in a baseline economy with no credit score heterogeneity, the rate cut results in a dampened consumption response.

Even though distributional issues are outside central banks' mandates, recent research provided evidence that wealth and income inequality affect the effectiveness of monetary policy. I show that the same rate cut stimulates aggregate consumption less in an economy with a higher proportion of borrowers with low credit scores and limited access to credit markets.

My model is the first one to identify refinancing heterogeneity by individuals with different credit scores and different MPCs, thus contributing to the newly emerging strand of literature that highlights the redistribution effects of monetary policy. Theoretical work in this strand includes Hedlund et al. (2017), Kaplan, Moll, and Violante (2018), Auclert (2019), Greg, Kurt, and L. (2020), Guren, Krishnamurthy, and Mcquade (2021).

The structure of this chapter is as follows. In section 2.2, I outline a refinancing model showing that credit score heterogeneity dampens housing wealth response to monetary policy. Section 2.3 concludes.

2.2 Model Outline

My continuous-time open economy model closely resembles a continuous-time open economy framework employed by Berger et al. (2021). Households are subject to idiosyncratic labor income risk and choose to consume or save in a liquid asset subject to a borrowing constraint, as in Aiyagari (1994). All households hold an FRM and are subject to aggregate interest rate risk. The mortgage rate in this model is a deterministic function of a 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. This simplification is consistent with empirical patterns and allows me to break down the household problem into two blocks: the decision on mortgage refinancing and the decision on consumption and savings.

Note that Berger et al. (2021) models endogenous relationship between short and mortgage rates. I abstract from redistribution between borrowers and lenders and focus on partial equilibrium outcomes for two reasons. First, lenders have much lower MPCs as compared to borrowers, significantly decreasing the impact of their returns on aggregate outcomes. Second, in my setting, such a model would generate a counterfactual relationship between mortgage rate and refinancing: lower credit score borrowers would receive lower mortgage rates. Instead, I assume that mortgage rates do not depend on credit scores to highlight the effect of credit scores beyond mortgage rates.

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

My analysis focuses on comparing the effect of monetary policy on refinancing, average coupons, and consumption in environments without and with credit score heterogeneity. I conclude that credit score heterogeneity dampens the effects of monetary policy by 11%.

2.2.1 Uncertainty

Households take into account two sources of uncertainty when making refinancing and consumption/savings decisions. First, households face idiosyncratic uncertainty in labor income. Second, they face aggregate uncertainty because the short-term interest rate and mortgage rates follow specific stochastic processes. I assume that the idiosyncratic process is independent of the aggregate process. [1]

Household h receives non-insurable idiosyncratic labor income Y_{ht} per unit of time, with lnY_{ht}

[1] Relaxing this assumption will reinforce my conclusions through an indirect effect of monetary policy explored in HANK literature.

following the continuous time Ornstein-Uhlenbeck process:

$$dlnY_{ht} = -\eta_y(lnY_{ht} - ln\bar{Y})dt + \sigma_y dZ_{ht} \tag{2.1}$$

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

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

$$dr_t = -\eta_r(r_t - \bar{r})dt + \sigma_r\sqrt{r_t}dZ_t \tag{2.2}$$

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:

$$m_t = \alpha_0 + \alpha_1 r_t \tag{2.3}$$

Thus, fluctuations in $m_t = m(r_t)$ arise from fluctuations in r_t in equilibrium.

2.2.2 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 the 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 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 $W_t + r_t W_t \mathbb{1}\{W_t < 0\} - F$. Households do not have any option to default.

Finally, we also assume that households face exogenous moving shocks that arrive at Poisson rate ν, forcing them to reset their mortgage coupon to the current market mortgage rate m_t.

2.2.3 Heterogeneity

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

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

It is important to note that even in the absence of heterogeneity in borrowing constraints on short-term debt, the differential arrival rate of refinancing shocks will dampen consumption response to an expansionary interest rate shock. Consider the following illustration. Consumption in this model is a function of income and wealth: $C = C(Y, W)$. The consumption response to mortgage rate shock is given by:[2]

$$\frac{\partial C}{\partial m} = MPC_y \frac{\partial Y}{\partial m} + MPC_w \frac{\partial W}{\partial m} \tag{2.4}$$

where $MPC_y = \frac{\partial C}{\partial Y}$ and $MPC_w = \frac{\partial C}{\partial W}$. In my setup aggregate uncertainty is orthogonal to idiosyncratic uncertainty, implying $\frac{\partial Y}{\partial m} = 0$. Let the probability of refinancing be $P(\text{Refi})$ and wealth in this state of the world be W^{Refi}. Denote wealth in the state of the world with no refinancing as W^{NoRefi}. Then the expected wealth can be written as follows:

$$E\left[W\right] = P(\text{Refi})\left[W^{Refi} - W^{NoRefi}\right] + W^{NoRefi} \tag{2.5}$$

Differentiation of (2.5) with respect to mortgage rate yields[3]

$$\frac{\partial E[W]}{\partial m} = \mathbb{E}\left[P(Refi)\frac{\partial}{\partial m}\left[W^{Refi} - W^{NoRefi}\right]\right] + \frac{\partial}{\partial m}E[W^{NoRefi}] \tag{2.7}$$

Note that the term $\mathbb{E}\left[\frac{\partial P(Refi)}{\partial m}\left[W^{Refi} - W^{NoRefi}\right]\right]$ disappears because in Calvo-style refinancing framework, refinancing probability does not respond to changes in interest rate. The two terms in the resulting expression are (i) the product of refinancing probability and marginal refinancing gain, and (ii) changes in wealth with no refinancing due to changes in mortgage rate.

Differential refinancing probabilities affect the covariance between refinancing probability and

[2] Since mortgage rate is a deterministic function of short rate, mortgage rate shock is qualitatively equivalent to monetary shock.

[3] The function inside the integral is differentiable since the $W^{Refi} - W^{NoRefi} = 0$ at $m = m^*$ and $\frac{\partial}{\partial m}\left[W^{Refi} - W^{NoRefi}\right] = 0$ at $m = m^*$ by value matching and smooth pasting conditions. Hence,

$$\begin{aligned}
\frac{\partial E[W]}{\partial m} &= \frac{\partial}{\partial m}\int_{-\infty}^{+\infty} \Delta W(m^*, m)\chi_C S \mathbb{1}\{m^* > m\} f(m^*) dm^* + \frac{\partial}{\partial m}E[W^{NoRefi}] = \\
&= \int_{-\infty}^{+\infty} \frac{\partial}{\partial m}\Delta W(m^*, m)\chi_C S \mathbb{1}\{m^* > m\} f(m^*) dm^* + \frac{\partial}{\partial m}E[W^{NoRefi}] = \\
&= E\left[\frac{\partial}{\partial m}\Delta W(m^*, m)\chi_C S \mathbb{1}\{m^* > m\}\right] + \frac{\partial}{\partial m}E[W^{NoRefi}] = \\
&= \mathbb{E}\left[\frac{\partial}{\partial m}\left[W^{Refi} - W^{NoRefi}\right]P(Refi)\right] + \frac{\partial}{\partial m}E[W^{NoRefi}]
\end{aligned} \tag{2.6}$$

marginal refinancing gain, which constitutes part of term (i) above. By assuming a higher probability to refinance for one group of agents, I induce them to have smaller and smaller gains from refinancing over time because more and more of them refinance into lower rates. Hence, the model with uniform refinancing probability across all agents will over-estimate wealth and hence consumption response to monetary shock.

Additional assumption of differential borrowing constraints affects the term MPC_w in (2.4). If higher credit score borrowers have higher borrowing limits, they can smooth their consumption more as compared to lower credit score borrowers, which implies lower MPC_w.

2.2.4 Household Problem

My partial equilibrium model has four state variables (W_h, r, m_h^*, Y_h). Liquid wealth W and stochastic income Y introduce uninsurable income risk and wealth heterogeneity. Outstanding mortgage rate m^* introduces a refinancing motive. Time-varying interest rates r provide a role for monetary policy. In what follows, I omit household-specific subscript h for brevity.

Households with identical constant relative risk aversion preferences with the 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:

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

subject to

$$dW_t = (Y_t - C_t + r_t W_t - m_t^* F)dt \tag{2.8}$$

$$W_t \geq b_j \tag{2.9}$$

$$dm_t^* = (m_t - m_{t-}^*) \left[\rho_t dN_t^{(\tau_{refi}^j)} + dN_t^{(\tau_{move})} \right] \tag{2.10}$$

and Y_t following (2.1), r_t following (2.2), and m_t following (2.3). Here τ_{refi}^j is the sequence of times when refinancing shock arrives to a household with credit score j, τ_{move} is the sequence of times the household is forced to move, and $N_t^{(\tau_{refi}^j)}$ and $N_t^{(\tau_{move})}$ correspond to changes in the corresponding counting processes.

Equation (2.8) governing the evolution of wealth: household receives labor income Y_t subject to uninsurable shocks, consumes, saves or borrows debt at short-term rate r_t, and pays outstanding coupon on the FRM $m_t^* F$. Equation (2.9) is a borrowing constraint on short-term debt – if $b_j = 0$, households with credit score j cannot take unsecured debt and can only save. Equation (2.10) implies that changes in m_t^* occur either due to the arrival of the refinancing shock, given that the current market mortgage rate is lower than the household's outstanding rate, or due to the arrival of the moving shock.

2.3 Calibration

In this subsection, I describe the model's calibrated parameters. These parameter choices are summarized in Table 2.1.

My calibration of the income process follows Floden and Lindé (2001), 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.

I view r_t as a short-term interest rate, and assume that the monetary authority adjusts these short rates. I follow Cox, Ingersoll, and Ross (1985) to estimate parameters of (2.2) using the generalized method of moments (GMM). I start with Euler discretization to obtain

$$\begin{aligned} r_{t+1} &= \alpha + \beta r_t + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= \sigma \sqrt{r_t} \sqrt{\Delta t} N(0,1) \end{aligned} \tag{2.11}$$

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

Table 2.1: 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_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_M	$15,000	borrowing limit for medium credit score group	assumption
b_H	$45,000	borrowing limit for high credit score group	b in baseline economy, given b_L, b_M

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

From (2.11) it follows that

$$\begin{aligned} E[\varepsilon_{t+1}] &= 0 \\ E[\varepsilon_{t+1}^2] &= \sigma^2 r_t \end{aligned} \tag{2.12}$$

Using (2.12) and orthogonality condition, one derives moment conditions $E[g(\kappa,\mu,\sigma)] = 0$, where

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

The corresponding sample moments are given by

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

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

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

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

This model is overidentified – there are four moment conditions and three parameters to estimate. I estimate GMM in two stages. First, I minimize the objective function using the identity weighting matrix. I 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. I use the Newey-West estimator of the spectral density matrix

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

where

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

This choice of weighting matrix results in asymptotically efficient estimates.

For my estimation I use daily data for 3-month Treasury yields from 1992 to 2019. This yields $T = 4003$ observations. I set $dt = 1/250$ and the number of lags in spectral density decomposition $k = 12$. The GMM estimates are $\eta_r = 28$ percent (corresponding to a half-life of 2.48 years) and $\sigma_r = 7$ percent. Given η_r and σ_r, I 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 I start my experiment.

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

I set the coefficient of relative risk aversion γ equal to 2, which is a standard calibration in the consumption-savings literature. I fix the mortgage balance F to the average in our data of \$225,230.

Discount parameter δ is calibrated to match the median wealth (excluding home equity) of homeowners in 2019 from Survey of Income and Program Participation (SIPP) data. The main homeowners for my sample period are Millenials, Generation X, and Baby Boomers. I weigh their wealth according to house purchase shares from "2021 National Association of Realtors Home Buyer and Seller Generational Trends." to arrive at 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.

I 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, I set χ=27 percent, which implies an average monthly refinancing frequency from 2000 to 2019 of 2 percent. I set the borrowing limit for this economy b to \$30,000 corresponding to the average credit card limit in 2019, according to Experian.[4]

In the model with credit score heterogeneity, I assume that credit score CS takes three values $CS \in \{L, M, H\}$. I limit the model to three credit score groups – low, middle, and high – which

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

occur with equal probability. I set $\chi_L = 0$ percent, restricting households from the lowest credit score group from refinancing. $\chi_M = 26.54$ percent, matching the average refinancing rate for borrowers with positive rate gaps and FICO score below 75^{th} percentile in the Fannie Mae data. I set $\chi_H = 54.49$ percent so that average refinancing rates are the same in baseline and heterogeneous economies.

I calibrate borrowing limits in the heterogeneous economy in the following way. I 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, I set $b_H = -\$45,000$.[5]

2.4 Solution

Households' consumption-savings decision and the evolution of the joint distribution g_t over state (W, r, m^*, Y) can be characterized with two differential equations: Hamilton-Jacobi-Bellman equation (HJB) and Kolmogorov Forward equation (KFE). In a stationary equilibrium, HJB and KFE

$$\begin{aligned}
\delta V(W, r, m^*, Y) = & \max_C u(C(W, r, m^*, Y)) + \mathcal{L}_r V + \mathcal{L}_Y V \\
& + (\nu + \chi_{CS} \mathbb{1}\{m(r) < m^*\}) \left[V(W, r, m(r), Y) - V(W, r, m^*, Y) \right] \\
& + \mu(W, r, m^*, Y) \partial_W V(W, r, m^*, Y)
\end{aligned} \tag{2.13}$$

$$\partial_t g_t = -\partial \left(\mu_W(W, r, m^*, Y) g_t \right) + \mathcal{L}_r^* g_t + \mathcal{L}_Y^* g_t - (\nu + \chi_{CS} \mathbb{1}\{m(r) < m^*\}) g_t \tag{2.14}$$

where $\mathcal{L}_r$ (respectively $\mathcal{L}_Y$) is the infinitesimal operator associated with the stochastic process r_t (respectively Y_t), $\mathcal{L}_r^*$ (respectively $\mathcal{L}_Y^*$) is the adjoint operator of $\mathcal{L}_r$ (respectively $\mathcal{L}_Y$), and $\mu(W, r, m^*, Y) = rW + Y - C(W, r, m^*, Y) - m^* F$ and $C(W, r, m^*, Y) = (u')^{-1}(V(W, r, m^*, Y))$ are optimal savings and consumption. Note that optimal consumption satisfies a usual first-order con-

[5] 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-third times quarterly labor income. This number is consistent with reported credit card borrowing limits in the Survey of Consumer Finances.

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

$$\partial_W V(b_{CS}, r, m^*, Y) \geq u'(V(b_{CS}, r, m^*, Y)) \tag{2.15}$$

2.4.1 HJB Equation

To solve a non-linear partial differential equation (PDE) for V, I use a finite difference method following Achdou et al. (2014). I denote $V_{k,i,m,j}$ the value function in aggregate state i (with r_i) for a household in idiosyncratic state j (with Y_j), with wealth W_k, and outstanding mortgage rate m_m^*. I approximate function $V_{k,i,m,j}$ at n_w discrete points in the space dimension, w_k, $k = 1, ..., n_w$. I use equispaced grids, denoting by Δ_w the distance between grid points of vector W. The derivative $\partial_W V(W_k, r_i, m_m^*, Y_j) = \partial_W V_{k,i,m,j}$ is approximated with either a forward or a backward difference approximation

$$\begin{aligned} \partial_W V_{k,i,m,j} &\approx \frac{V_{k+1,i,m,j} - V_{k,i,m,j}}{\Delta_w} \equiv \partial_W V_{k,i,m,j,F} \\ \partial_W V_{k,i,m,j} &\approx \frac{V_{k,i,m,j} - V_{k-1,i,m,j}}{\Delta_w} \equiv \partial_W V_{k,i,m,j,B} \end{aligned} \tag{2.16}$$

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

$$\begin{aligned} \partial_W V_{k,i,m,j} = \partial_W V_{k,i,m,j,F} \mathbb{1}\{\mu_{k,i,m,j,F} > 0\} + \partial_W V_{k,i,m,j,B} \mathbb{1}\{\mu_{k,i,m,j,B} < 0\} \\ + \partial_W \bar{V}_{k,i,m,j} \mathbb{1}\{\mu_{k,i,m,j,F} \leq 0 \leq \mu_{k,i,m,j,B}\} \end{aligned} \tag{2.17}$$

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

$$\begin{aligned}
\partial_r V_{k,i,m,j,F} &\equiv \frac{V_{k,i+1,m,j} - V_{k,i,m,j}}{\Delta_r} \\
\partial_r V_{k,i,m,j,B} &\equiv \frac{V_{k,i,m,j} - V_{k,i-1,m,j}}{\Delta_r} \\
\partial_{rr}^2 V_{k,i,m,j} &\equiv \frac{V_{k,i+1,m,j} - 2V_{k,i,m,j} + V_{k,i-1,m,j}}{(\Delta_r)^2}
\end{aligned} \tag{2.18}$$

$$\begin{aligned}
\partial_Y V_{k,i,m,j,F} &\equiv \frac{V_{k,i,m,j+1} - V_{k,i,m,j}}{\Delta_Y} \\
\partial_Y V_{k,i,m,j,B} &\equiv \frac{V_{k,i,m,j} - V_{k,i,m,j-1}}{\Delta_Y} \\
\partial_{YY}^2 V_{k,i,m,j} &\equiv \frac{V_{k,i,m,j+1} - 2V_{k,i,m,j} + V_{k,i,m,j-1}}{(\Delta_Y)^2}
\end{aligned} \tag{2.19}$$

The boundary condition (2.15) is enforced by setting

$$\partial_W V_{1,i,m,j,B} = u'(V(b_{CS}, r, m^*, Y)) \tag{2.20}$$

The finite difference approximation to (2.13) is

$$\begin{aligned}
\frac{V_{k,i,m,j}^{n+1} - V_{k,i,m,j}^{n}}{\Delta_t} + \delta V_{k,i,m,j}^{n+1} = {} & u(C_{k,i,m,j}^{n}) + (\nu + \chi_{CS} \mathbb{1}\{m(r) < m^*\}) \left(V_{k,i,i,j}^{n+1} - V_{k,i,m,j}^{n+1}\right) \\
& + \partial_W V_{k,i,m,j,F}^{n+1} \left[\mu_{k,i,m,j,F}^{n}\right]^{+} + \partial_W V_{k,i,m,j,B}^{n+1} \left[\mu_{k,i,m,j,B}^{n}\right]^{-} \\
& + \partial_r V_{k,i,m,j,F}^{n+1} \left[\mu(r_k)\right]^{+} + \partial_r V_{k,i,m,j,B}^{n+1} \left[\mu(r_k)\right]^{-} + \partial_{rr}^2 V_{k,i,m,j}^{n+1} \frac{\sigma^2(r_k)}{2} \\
& + \partial_Y V_{k,i,m,j,F}^{n+1} \left[\mu(Y_j)\right]^{+} + \partial_Y V_{k,i,m,j,B}^{n+1} \left[\mu(Y_j)\right]^{-} + \partial_{YY}^2 V_{k,i,m,j}^{n+1} \frac{\sigma^2(Y_j)}{2}
\end{aligned} \tag{2.21}$$

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

Equation (2.21) constitutes a system of $n_w \times n_r \times n_{m^*} \times n_Y$ equations, and can be written in

Figure 2.1: Visualization of the Part of Intensity Matrix A

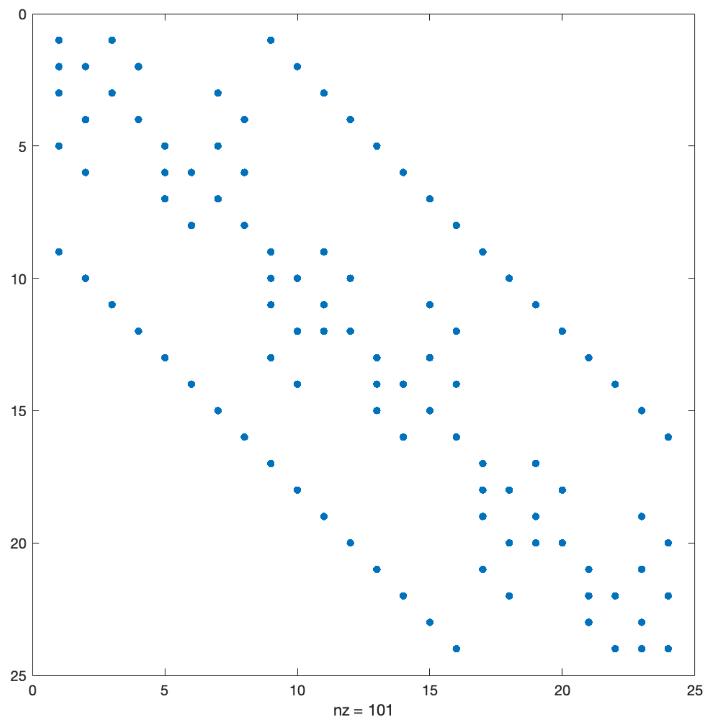


Figure displays visualization of the matrix A with $n_w = 2$, $n_r = n_{m^*} = 2$, $n_Y = 3$. See text for details.

matrix notation

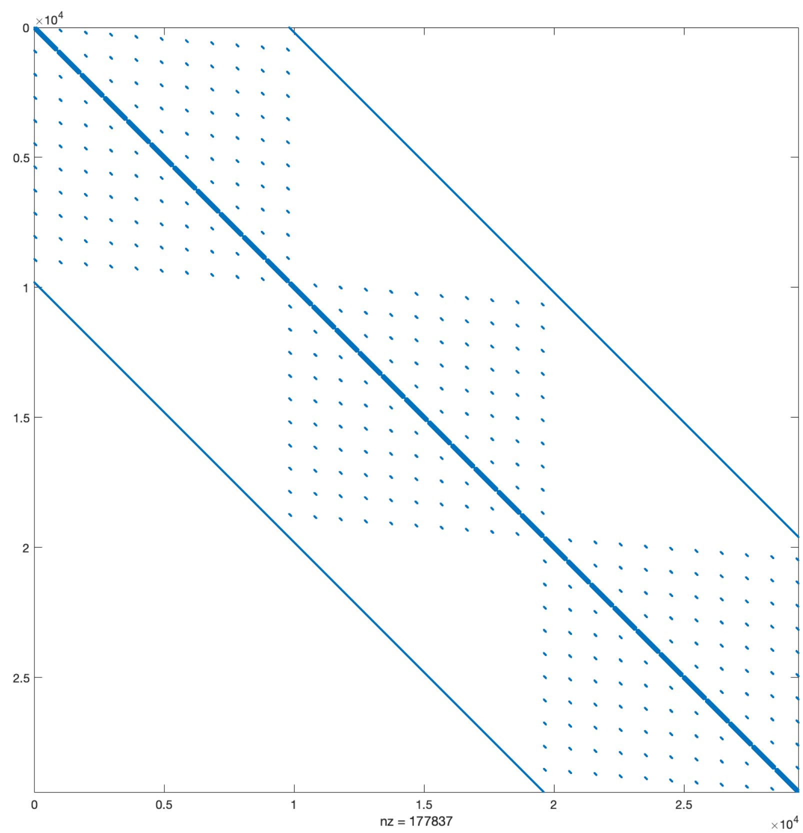
$$\frac{1}{\Delta_t}(V^{n+1} - V^n) + \delta V^{n+1} = u^n + A^n V^{n+1} \tag{2.22}$$

where u^n is a vector with elements $\{u(C^n_{k,i,m,j})\}$, A^n is the intensity matrix that encodes the evolution of the stochastic process of all state variables, and V^{n+1} is the unknown value vector. A^n satisfies all the properties of a Poisson transition matrix: all rows sum to zero, diagonal elements are non-positive and off-diagonal elements are non-negative. Figure 2.1 plots the visualization of the matrix A with $n_w = 2$, $n_r = n_{m^*} = 2$, $n_Y = 3$, and the figure 2.2 plots it for our final specification of the grid with $n_w = 81$, $n_r = n_{m^*} = 11$, $n_Y = 3$.

The solution algorithm can be summarized as follows. Formulate an initial guess. A natural initial guess is

$$V^0_{k,i,m,j} = \frac{u(Y_j + r_i W_k - m^*_m F)}{\delta} \tag{2.23}$$

Figure 2.2: Visualization of the Intensity Matrix A



The figure displays visualization of the matrix A with $n_w = 81$, $n_r = n_{m^*} = 11$, $n_Y = 3$. See text for details.

For $n = 1, 2, \ldots$ follow

1. Compute $\partial_W V_{k,i,m,j}$ using (2.16), (2.17), (2.18), (2.19)

2. Compute $C^n_{k,i,m,j} = (u')^{-1}(V(W, r, m^*, Y))$

3. Compute V^{n+1} using (2.22)

4. If V^{n+1} is close enough to V^n, stop. Otherwise, go to step 1.

2.4.2 KFE Equation

To compute impulse response functions, I approximate the density at $n_w \times n_r \times n_Y$ discrete points. Given initial condition g^0, the KFE 2.14 is iteratively solved by solving the following system:

$$\frac{g^{n+1} - g^n}{\Delta_t} = (A^n)^T g^{n+1} \tag{2.24}$$

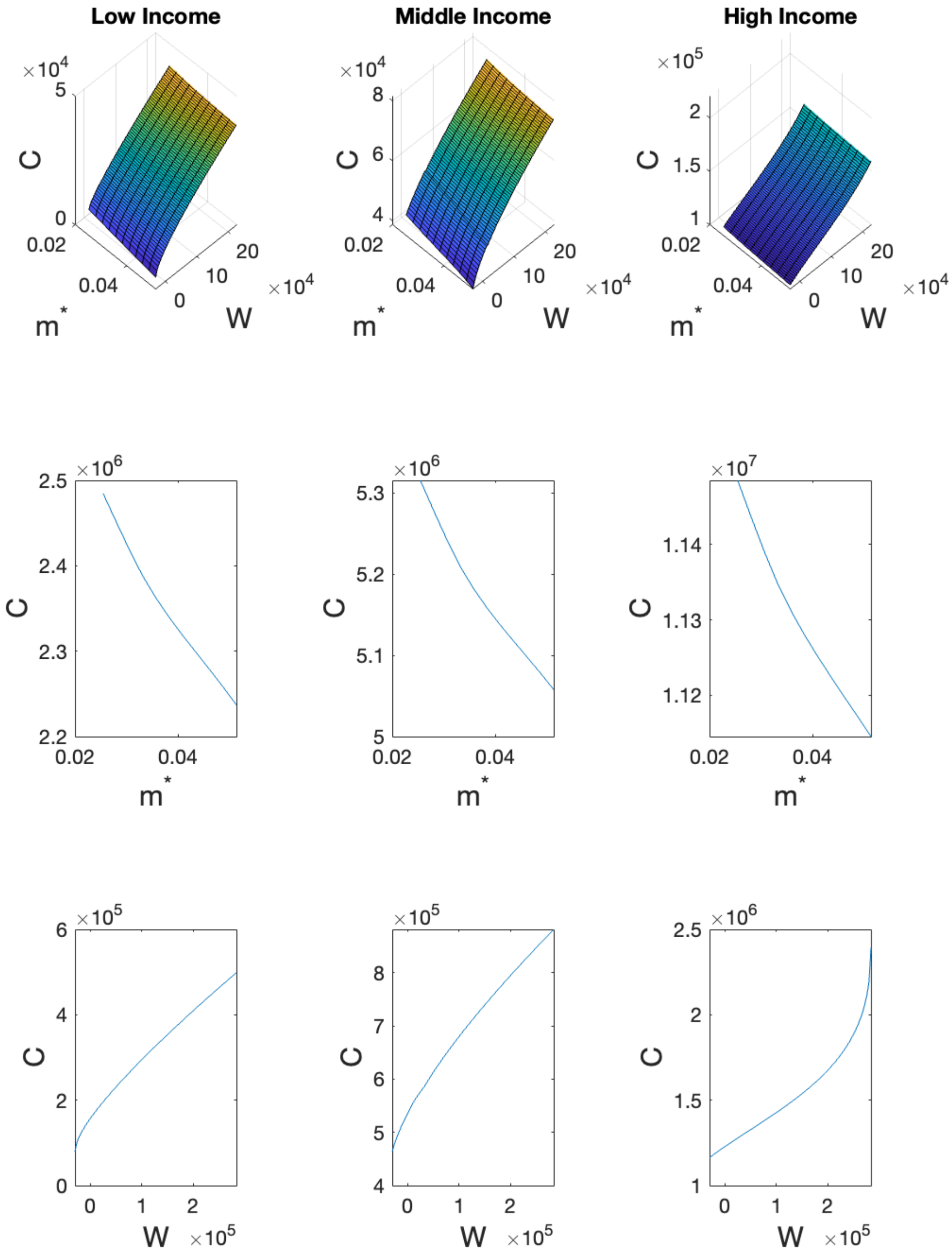
where $(A^n)^T$ is the transpose of the intensity matrix A^n.

2.5 Steady State

The steady state in my setup features cross-sectional heterogeneity in three variables: W, m^*, and Y. Figure 2.3 plots the steady state consumption function for a baseline economy with no credit score heterogeneity. From left to right, each panel represents a different income state. Consumption is decreasing in the outstanding mortgage rate and decreasing in wealth. In Figures 2.4, 2.5, and 2.6, I provide steady state consumption functions for each credit score group, which are qualitatively in line with the baseline setup.

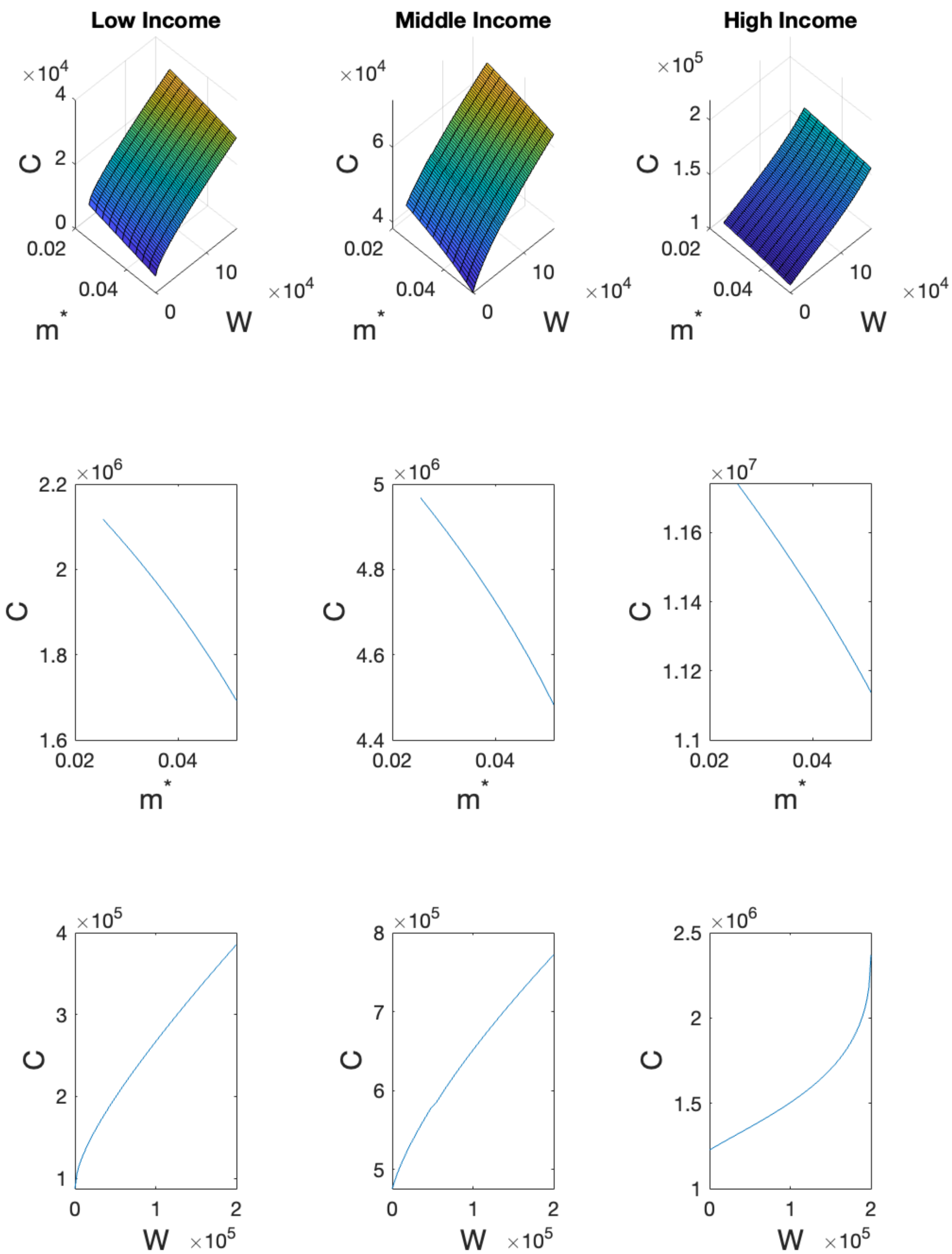
Table2.2 summarizes the model's steady state. The first row lists average consumption. Average consumption is comparable across the two economies and is less than the average income due to debt repayment. The second row lists the average MPC out of liquid wealth. The baseline economy features an average MPC of 0.33, and the heterogeneous economy - that of 0.37. Households in the low credit score group have the highest MPCs with an average of 0.47, whereas these

Figure 2.3: Steady State Consumption Function in the Baseline Economy



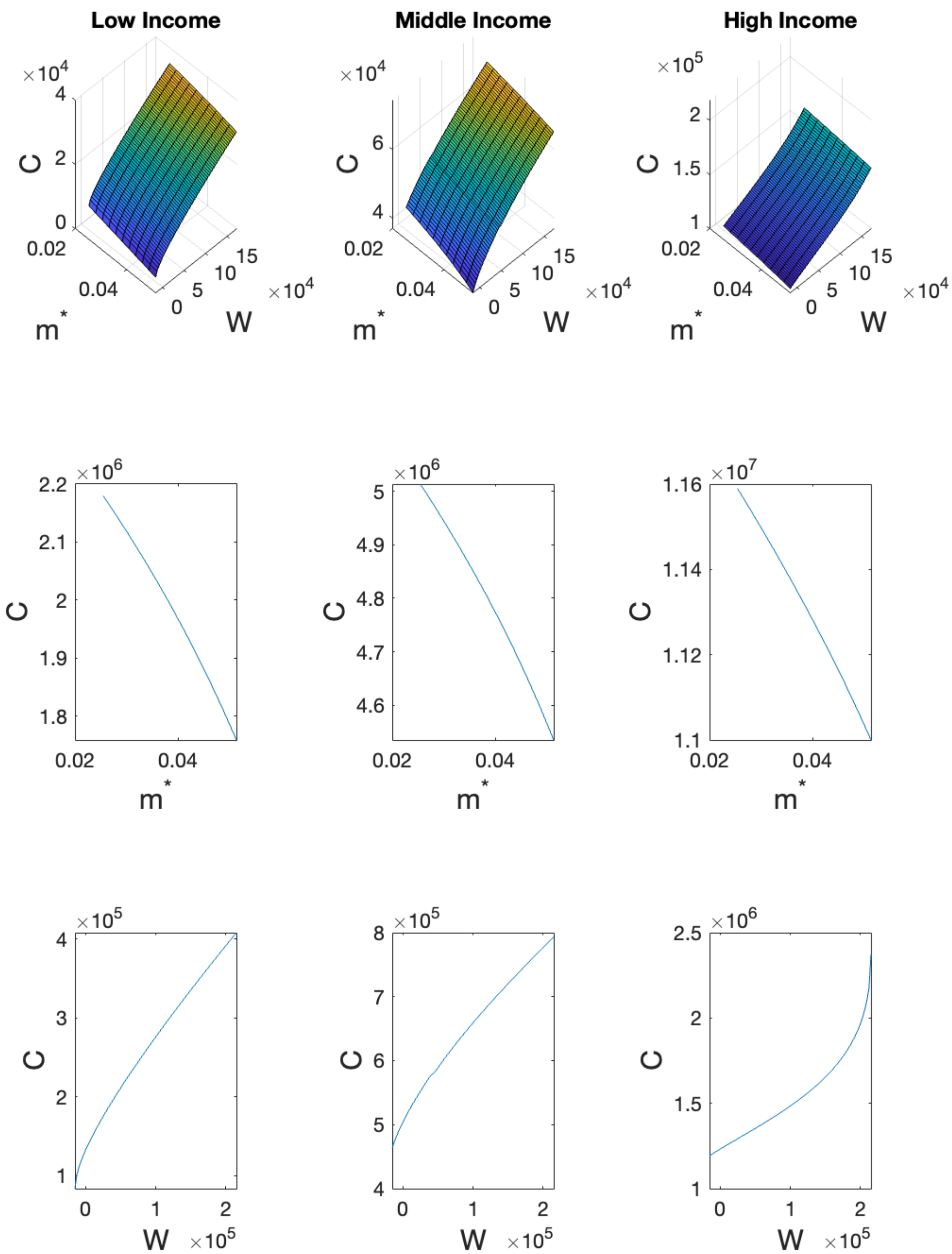
The figure displays steady state consumption as a function of income, outstanding mortgage rate, and liquid wealth. See text for details.

Figure 2.4: Steady State Consumption Function for Low Credit Score Households



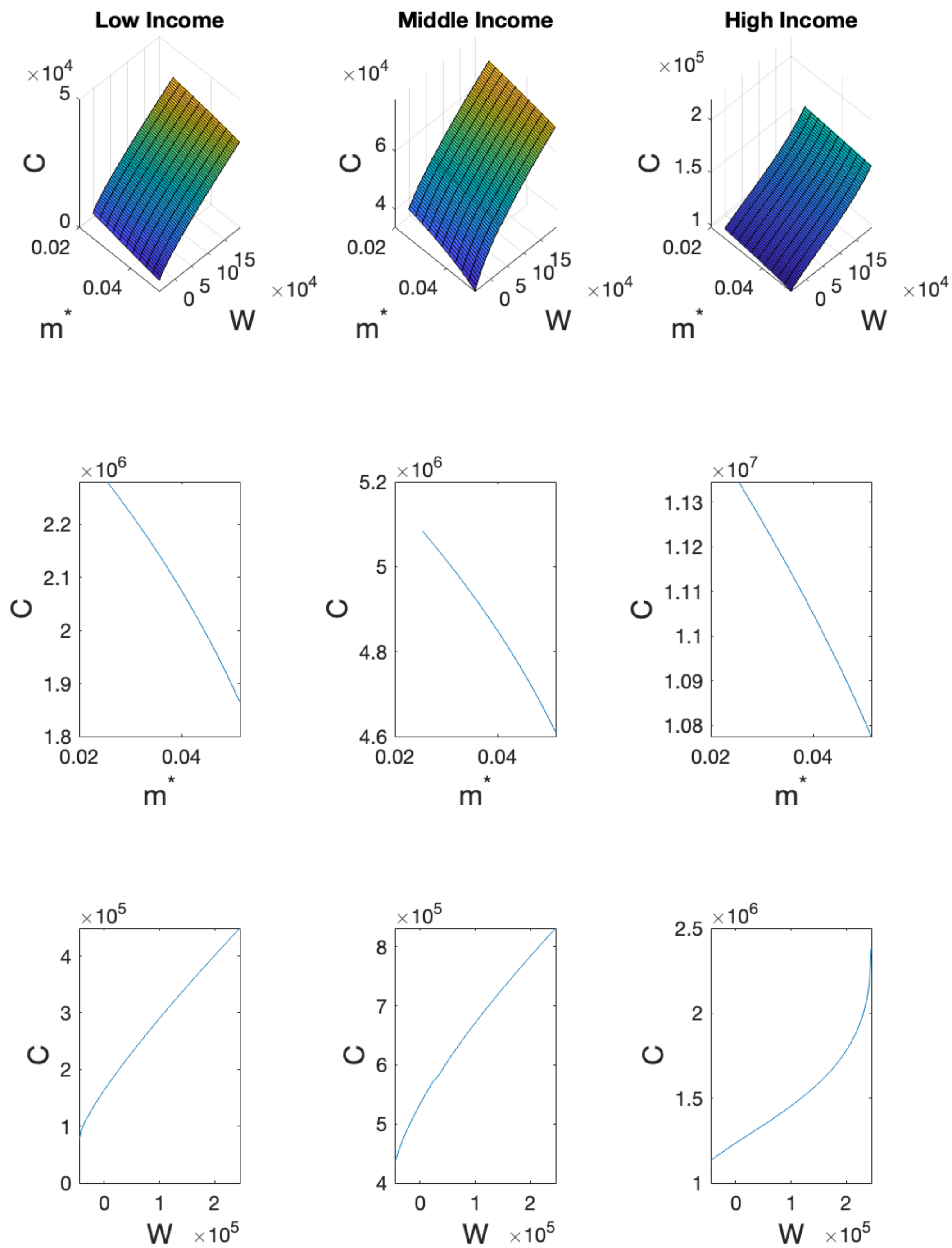
The figure displays steady state consumption as a function of income, outstanding mortgage rate, and liquid wealth for low credit score households. See text for details.

Figure 2.5: Steady State Consumption Function for Medium Credit Score Households



The figure displays steady state consumption as a function of income, outstanding mortgage rate, and liquid wealth for medium credit score households. See text for details.

Figure 2.6: Steady State Consumption Function for High Credit Score Households



The figure displays steady state consumption as a function of income, outstanding mortgage rate, and liquid wealth for high credit score households. See text for details.

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%).

2.6 Monetary Policy Experiment

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

The top row of Figure 2.7 shows the impulse response functions (IRFs) of mortgage rate and average coupon in the baseline economy and economy with credit score heterogeneity. The 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 2.7 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, the initial refinancing impulse declines faster in the 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. an 11 percent increase over the baseline.

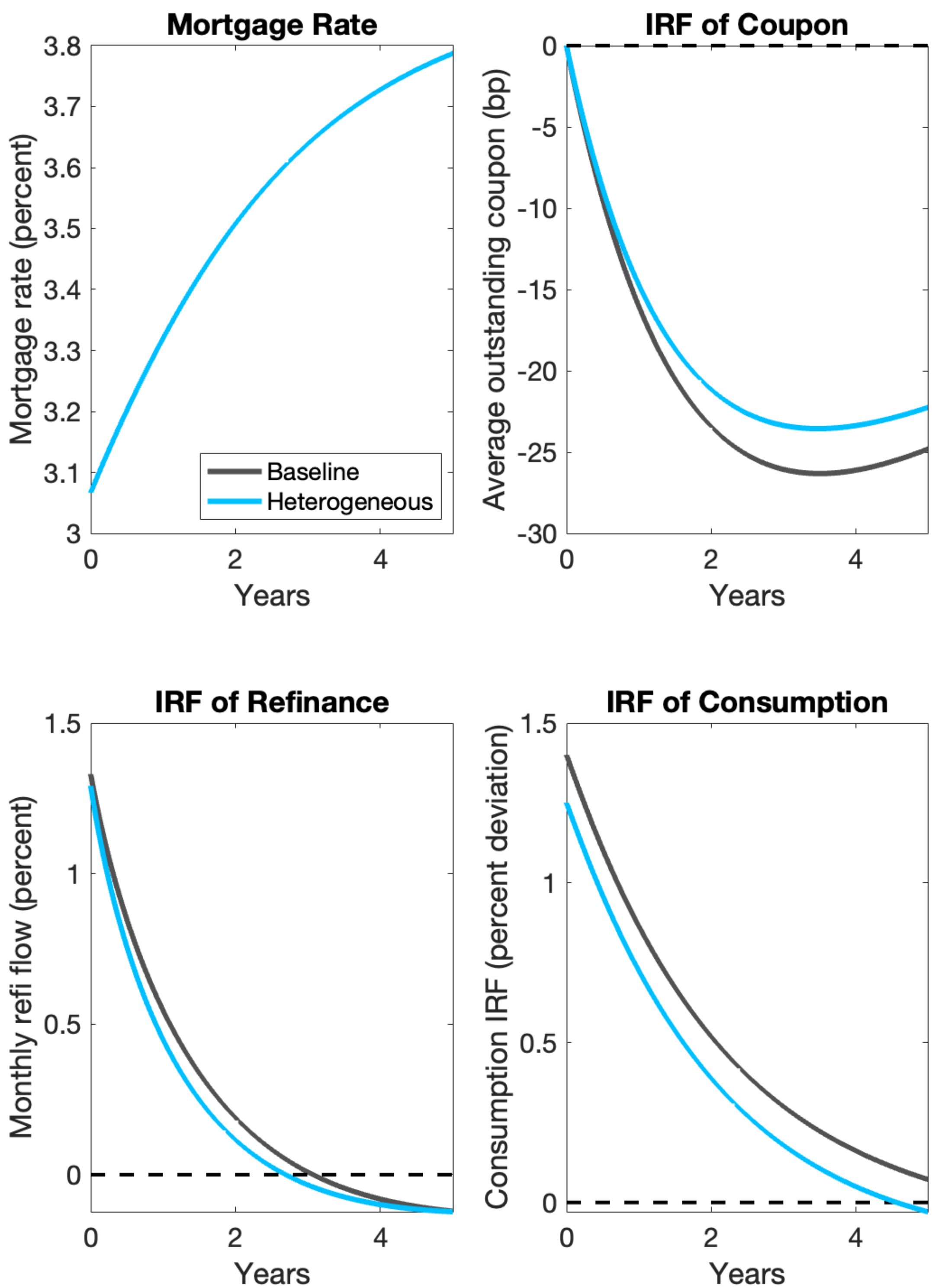
Heterogeneous economy is less responsive to monetary policy because low credit score house-

Table 2.2: 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%

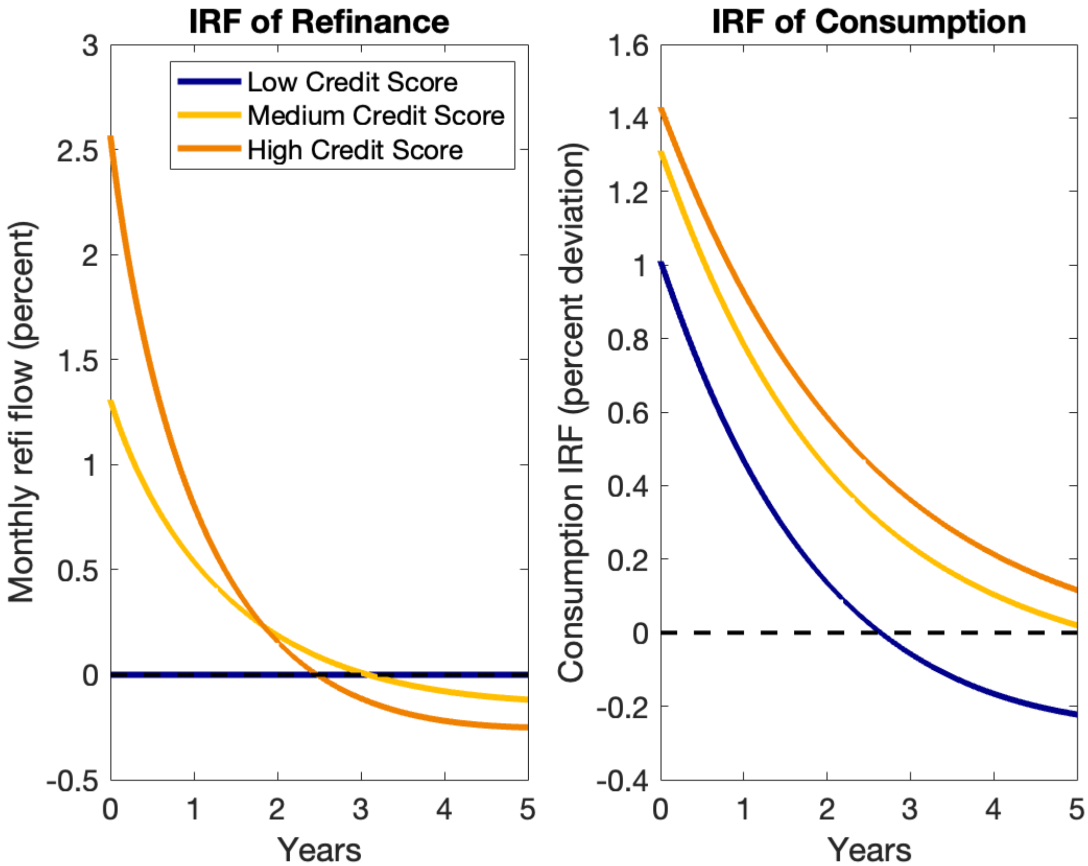
The table summarizes household consumption, expenditure, and saving behavior in the steady state.

Figure 2.7: Refinancing and Consumption Response to Monetary Policy



The 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 2.8: Refinancing and Consumption Response to Monetary Policy in Heterogeneous Economy



The 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.

holds, who cannot borrow and refinance, have the highest marginal propensities to consume. To show that the low credit score group has a significantly lower consumption response than other groups, in Figure 2.8 I decompose refinancing and consumption response by credit score group. On impact, households in the 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 the substitution effect, and no income effect, since we abstract from the effect of monetary policy on income in this setup. The intertemporal substitution effect of a rate cut induces households 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 to 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, I isolate the wealth effect, by shutting refinancing down in both economies. This decomposition is displayed in Table 2.3. Each cell in the first row represents the on-impact consumption elasticity in the model without refinancing. In a homogeneous economy, 15% of total consumption response can be attributed to the refinancing channel. In a heterogeneous economy, where households have differential borrowing constraints, only 10% of the total response is through the refinancing channel. The refinancing channel in the low credit score group is 0 by construction, so the increase in consumption for this group is driven by the wealth effect only.

Credit score heterogeneity dampens both wealth and refinancing channels because medium and high credit scores have lower MPCs than low credit score borrowers. First, the differential borrowing limits affect the 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 can borrow. Second, the refinancing effect benefits higher credit score households by less than medium credit score households.

2.7 Conclusion

In the first two chapters of my dissertation, I delivered detailed results on credit score heterogeneity of refinance response to monetary policy. Using Fannie Mae Single-Family Loan-Level historical data, I estimated that a 1 percentage point increase in the rate gap increases the refinancing probability for borrowers with a FICO credit score of 800 twice as much as that for borrowers with a FICO score of 700. The refinancing model I employ suggests that this heterogeneity is

Table 2.3: 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

The table decomposes the channels through which 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.

economically significant – the aggregate consumption response to monetary policy on impact is approximately 11% lower than in a standard model with only mortgage rate heterogeneity.

Chapter 3: Anchoring of Inflation Expectations: An Empirical Test

Joint work with A. Burya and S. Mishra.

3.1 Introduction

Many central banks have adopted a formal inflation-targeting framework based on the theoretical predictions that an explicit numerical objective for the level of inflation would help anchor long-term inflation expectations. In a simple case, a central bank policy announcement of an interest rate change leads to an adjustment in the market price of the corresponding assets. When the central bank follows an inflation-targeting policy, the mechanism works similarly. The markets view the central bank's inflation-targeting objective as its commitment to apply certain policies when required to keep inflation stable. Empirically verifying the success of inflation-targeting regimes has been difficult as survey data on long-term inflation expectations tend to be of limited availability and low frequency.

This chapter uses market-based measures of inflation expectations derived from daily bond yield data to show that the long-term inflation expectations in the U.S. are anchored. In particular, we show the sensitivity of inflation expectations to monetary policy is lower if markets *ex-ante* expect the Fed to respond to inflation more aggressively. The intuition behind the mechanism is as follows. During news releases related to inflation, markets revise their expectations about (i) future inflation and (ii) the Fed's reaction to inflation during the next FOMC meeting. The Fed's FOMC announcement leading to a rate change higher than the one expected from the inflation news release indicates that the markets expect the Fed to react more aggressively in the future. If inflation expectations are anchored, markets will not adjust inflation expectations as much.

To show that the response of inflation expectations to monetary policy is lower when markets expect the Fed's reaction to inflation to be more aggressive, we proceed in two steps. First, we measure market expectations about the Fed's reaction to inflation as a residual from the regression of the expected future policy rate on inflation expectations around the CPI release dates. Second, we estimate inflation expectations' sensitivity to monetary policy conditional on the expected Fed's aggressiveness.

We use a simplified version of the monetary policy reaction function from Bauer and Swanson (2023) to illustrate our approach. Let

$$i_t^{pol} = \phi_t \pi_t + MP_t \tag{3.1}$$

where i_t^{pol} denotes the policy rate at time t, π_t denotes the inflation rate at time t, ϕ_t describes the Fed's aggressiveness to inflation,[1] and MP_t denotes a monetary policy shock or exogenous random deviation from the Fed's reaction function $\phi_t \pi_t$. Due to the Fed's inflation targeting objective, aggressiveness ϕ_t is positive and time-varying. A positive inflation shock leads to an increase in interest rates by the Fed. In the standard model like the Taylor rule, ϕ_t is constant because the degree of monetary aggressiveness is assumed to not vary over time. However, the degree of the Fed's aggressiveness to inflation varies over time (see Bauer and Swanson (2023) for details). When the Fed is pursuing inflation targeting, an inflation shock of the same magnitude will lead to a more aggressive policy response (larger ϕ_t).

From the reaction function (3.1) it follows that there are three possible sources of changes in the expected future policy rate over time horizon h: (1) changes in expectations of future inflation; (2) changes in the expectations of the Fed's aggressiveness; (3) changes in the expectations of monetary policy shock:

$$\Delta\mathbb{E}_t i_{t,h}^{pol} = \mathbb{E}_t \phi_{t,h} \times \Delta\mathbb{E}_t \pi_{t,h} + \Delta\mathbb{E}_t \phi_{t,h} \times \mathbb{E}_t \pi_{t,h} + \Delta\mathbb{E}_t MP_{t,h} \tag{3.2}$$

[1] In what follows, we use the terms "the Fed's responsiveness to inflation", "the Fed's aggressiveness", and ϕ_t interchangeably.

where $\mathbb{E}_t i^{pol}_{t,h}$ is the time t expected policy rate over horizon h, $\mathbb{E}_t \pi_{t,h}$ is the time t average expected inflation rate over h, $\mathbb{E}_t \phi_{t,h}$ is the time t expected aggressiveness of the Fed over h, and $\mathbb{E}_t MP_{t,h}$ is the expected monetary policy over h.

In the first step of our analysis, we identify changes in market expectations about the Fed's aggressiveness to inflation for each horizon h, $\Delta\mathbb{E}_t \phi_{t,h}$, by estimating residuals from an empirical counterpart of equation (3.2) at Consumer Price Index (CPI) news release dates τ:

$$\Delta i^{pol,e}_{\tau,h} = \alpha \Delta \pi^e_{\tau,h} + \varepsilon_\tau \tag{3.3}$$

where $i^{pol,e}_{\tau,h}$ is the time τ measure of the expected future policy rate over horizon h, and $\pi^e_{\tau,h}$ is the time τ measure of the average expected future inflation over h. Since at CPI release dates markets do not expect monetary shocks (unless the CPI release date coincides with the FOMC date), residual from this regression adjusted for expected inflation, $\tilde{\varepsilon}_\tau = \frac{\hat{\varepsilon}_\tau}{\pi^e_{\tau,h}}$, provides an estimate of $\Delta\mathbb{E}_\tau \phi_{\tau,h}$. Positive $\tilde{\varepsilon}$ implies that markets have revised their expectations about the Fed's aggressiveness toward inflation upward.

In the second step, we show that inflation expectations react to monetary policy news less if the markets revised their expectations about the Fed's aggressiveness upward. In other words, we estimate the inflation expectations' sensitivity to monetary policy conditional on the expectations about the Fed's aggressiveness by running the following regression:

$$\Delta \pi^e_{t,h} = \beta MP^s_t + \gamma \tilde{\varepsilon}_\tau + \delta MP^s_t \times \tilde{\varepsilon}_\tau + u_t \tag{3.4}$$

where MP^s_t is a measure of a monetary policy shock. The coefficient δ represents the differential market response to monetary policy based on expectations about the Fed's aggressiveness. The sum $\beta + \delta$ corresponds to the inflation expectations' sensitivity to monetary policy shocks. If inflation expectations decrease after a monetary tightening ($\beta + \delta < 0$), given that the Fed is expected to have a stronger response to inflation ($\tilde{\varepsilon}_t$ is positive), a positive δ implies that inflation expectations adjust less. This means that the effect of monetary policy on inflation expectations is "undone" and hence inflation expectations are anchored. If the Fed is thought to pursue a stronger response to control inflation, then the markets do not respond as much to the current policy shocks.

The rest of this chapter is organized as follows: in section 3.2 we review the related literature, section 3.3 describes the data, section 3.4 describes the construction of all the market-based measures of expectations needed for analysis, section 3.5 contains the empirical results, and section 3.6 concludes.

3.2 Related Literature

This chapter contributes to the broad literature that studies the effect of economic news on asset prices by using high-frequency data and market-based measures of expectations.

One strand of this literature focuses on the effect of macroeconomic news on inflation compensation. Gürkaynak, Levin, and Swanson (2010) show that inflation compensation in the U.S., a country without an explicit inflation target, exhibits higher responsiveness to economic news than that in the United Kingdom, a country with an explicit inflation target.[2] Gürkaynak, Levin, and Swanson (2010) find that far-ahead nominal forward rates are quite sensitive to news due to the variation in inflation expectations. In contrast, Beechey and Wright (2009) estimate only a small response of forward inflation compensation to real-side macroeconomic news. Bauer (2014) finds that inflation compensation exhibits strong sensitivity to macroeconomic surprises, both for price-level news and real-side news. The reason for this is that intraday data, although more precise, mask the slightly delayed response to the announcements.

Another strand of this literature focuses on the effect of monetary policy news on asset prices. The findings not consistent with the standard economic theory were attributed to the "Fed Information Effect". Romer and Romer (2000) show that the Fed's information about expected inflation that is not available to private forecasters can be inferred from their interest rate changes. Campbell et al. (2012) provide evidence for the "Fed Information Effect" by documenting that monetary

[2]The research on emerging economies usually employs low-frequency panel data and arrive to the opposite conclusion about the effects of inflation targeting. For example, Stojanovikj and Petrevski (2021) show that in emerging economies, inflation targeting is associated with lower average inflation (that has negligible favorable effects, as compared to alternative monetary strategies), but it does not lower inflation volatility.

policy contraction is associated with a significant downward revision in Blue Chip forecasts of unemployment. Nakamura and Steinsson (2018) show that monetary policy contraction is associated with a significant upward revision in Blue Chip GDP forecasts. Lunsford (2020) analyzes the Fed's forward guidance announcements from 2000–2006 and finds evidence of a "Fed Information Effect" in the period from 2000–2005, but not afterward.

The closely related paper to ours is by Bauer and Swanson (2023) who find a similar effect as Lunsford (2020) and present an alternate channel called the "Fed Response to News" channel which can also explain the empirical results from Nakamura and Steinsson (2018). The main idea is that incoming, publicly available economic news causes both the Fed to change monetary policy and the private sector to revise its forecasts. Their empirical strategy includes economic news on GDP, unemployment, CPI, etc., and shows that it is not only strongly correlated with Blue Chip forecast revisions, but also with high-frequency monetary policy surprises which arrive after the economic news. This is explained by the fact that markets do not have full information about the Fed's reaction function ex-ante. This leads to the predictability of monetary policy surprises ex-post, even if these surprises were unpredictable ex-ante. Our methodology follows this channel in using CPI release news revealed before the FOMC meeting that is not immediately incorporated into the rates.

Our contribution is two-fold. First, we provide a new way to estimate the expected aggressiveness of the Fed. Second, we document the dampened effect of forward guidance conditional on the expected Fed's aggressiveness.

3.3 Data

We employ the daily continuously compounded zero-coupon Treasury Inflation-Protected Securities (TIPS)[3] yields as measures of real interest rates and breakeven inflation rates as measures of inflation expectations. For both, we use data constructed by Gürkaynak, Sack, and Wright

[3]TIPS are fixed-income securities whose coupons and principal payments are indexed to the non-seasonally adjusted CPI for all urban consumers.

(2010). This data set is available for download on the Board of Governors' website.[4] The data spans maturities from 2 to 20 years. We start our sample period on January 1, 2005, to avoid relying on data from the period when TIPS liquidity was limited. We end our sample on June 30, 2019.

Table 3.1 reports summary statistics of nominal Treasury yields, TIPS yields, and TIPS inflation compensation from Gürkaynak, Sack, and Wright (2010) data. Nominal and real yield curves and inflation compensation curves are upward-sloping. The skewness of inflation compensation is negative over all horizons but becomes less negative for longer maturities. The excess kurtosis, however, is positive and decreasing in maturity.

Table 3.1: Summary Statistics of the Gürkaynak, Sack, and Wright (2010) Data

	Mean	St. Dev.	Min	Max	Skewness	Excess Kurtosis
	Panel A: U.S. Treasury Nominal Interest Rates					
i_2	1.74	1.44	0.16	5.25	0.93	-0.35
i_5	2.46	1.17	0.59	5.13	0.50	-0.76
i_{10}	3.32	1.06	1.40	5.29	0.07	-1.38
i_{20}	3.92	1.03	1.85	5.97	-0.00	-1.41
	Panel B: TIPS Yields					
r_2^{TIPS}	0.12	1.29	-2.20	5.48	0.93	1.91
r_5^{TIPS}	0.59	1.07	-1.71	3.91	0.14	-0.47
r_{10}^{TIPS}	1.15	0.90	-0.85	3.75	-0.07	-0.83
r_{20}^{TIPS}	1.57	0.75	0.05	3.32	-0.06	-1.37
	Panel C: TIPS Inflation Compensation					
IC_2^{TIPS}	1.62	0.96	-4.89	3.22	-2.72	12.52
IC_5^{TIPS}	1.87	0.58	-1.78	2.90	-2.33	9.54
IC_{10}^{TIPS}	2.17	0.41	0.17	3.00	-0.97	1.46
IC_{20}^{TIPS}	2.35	0.45	0.82	3.38	-0.50	-0.27
N				4,121		

The table shows summary statistics from Gürkaynak, Sack, and Wright (2010) data between January 1, 2005, and June 30, 2019.

[4] Available at `https://www.federalreserve.gov/econres/feds/the-tips-yield-curve-and-inflation-compensation.htm`.

To construct monetary policy shocks, we use the dates of FOMC meetings for our sample period from Nakamura and Steinsson (2018)[5] and daily data on Federal funds futures, three-month Eurodollar futures, Treasury bond yields at maturities of 2-, 5- and 10-years from the Bloomberg terminal.

To construct changes in the expected aggressiveness of the Fed, we use the CPI news release dates from the Bureau of Labor Statistics.[6]

3.4 Market-Based Measures of Expectations

The ultimate goal of this paper is to measure the sensitivity of inflation expectations to monetary policy conditional on market expectations of the Fed's reaction function. To measure expectations of the Fed's reaction function we additionally need a measure of the expected future policy rate. In this section, we describe the construction of market-based measures of (i) inflation expectations, (ii) monetary policy, (iii) expectations of the future policy rate, and (iv) the expectations of the Fed's aggressiveness.

3.4.1 Inflation Expectations

Market-based measures of inflation expectations provide a rich source of information to investors, policymakers, and researchers. One of them is inflation compensation defined as the difference between the interest rates on nominal and inflation-indexed bonds:

$$IC_{t,h} = i_{t,h} - r_{t,h} \tag{3.5}$$

where $i_{t,h}$ is the nominal interest rate for a zero-coupon bond of maturity h, $r_{t,h}$ is the real interest rate for a zero-coupon bond of maturity h, and $IC_{t,h}$ is inflation compensation for the same maturity.

[5] We cross reference and verify these dates from the Board of Governors' website at `http://www.federalreserve.gov/monetarypolicy/fomccalendars.html`.

[6] Available at `https://www.bls.gov/schedule/news_release/cpi.htm`.

It is important to note that due to the risk of changes in inflation, inflation compensation is a noisy measure of inflation expectations. By standard economic theory

$$i_{t,h} = r_{t,h} + \mathbb{E}_t\pi_{t,h} + IRP_{t,h} \tag{3.6}$$

where $\mathbb{E}_t\pi_{t,h}$ is expected future inflation over h, and $IRP_{t,h}$ is an inflation risk premium. It measures the compensation that investors demand to cover the expected rate of future inflation and the risks associated with the uncertainty of future inflation at a given horizon and depends on the covariance between inflation and economic activity.

The most widely used real-time proxy for inflation expectations in the U.S. is the "break-even inflation rate" (BEI) equal to the spread between yields on nominal Treasury securities and on TIPS of comparable maturities.

However, even though the market for TIPS has grown substantially since its inception in 1997, the TIPS yield exceeds the true real interest rate due to the TIPS liquidity premium:

$$r_{t,h}^{TIPS} = r_{t,h} + LRP_{t,h}^{TIPS} \tag{3.7}$$

where $r_{t,h}^{TIPS}$ is the yield on TIPS, and $LRP_{t,h}^{TIPS}$ is the TIPS liquidity premium.

Consequently, TIPS inflation compensation or BEI can be written as

$$IC_{t,h}^{TIPS} = \mathbb{E}_t\pi_{t,h} + IRP_{t,h} - LRP_{t,h}^{TIPS} \tag{3.8}$$

which implies that BEI deviates from inflation expectations either due to inflation risk premium or TIPS liquidity premium.

The ultimate goal of this paper is to measure the sensitivity of inflation expectations to monetary policy conditional on market expectations of the Fed's reaction function. That exercise will ideally require applying risk premia adjustments to BEI rates.

Nevertheless, we employ BEI as a measure of inflation expectations and leave the risk premia adjustments for future research. Besides the fact that all estimates of the inflation risk premium and liquidity premium in the literature are highly model-dependent, there is vast empirical evidence suggesting that risk premia vary at business-cycle frequencies, implying that they will be differenced out in the daily bond yield analysis.[7]

Bauer and Swanson (2023) show that economic news predicts high-frequency monetary policy surprises. As per the Full Information Ration Expectations (FIRE) assumption, markets would already incorporate all the publicly available information up until the time of the trade. So, under FIRE, the only reason why Bauer and Swanson (2023) find the predictability of high-frequency monetary policy surprises is the time-varying risk premia. But, Piazzesi and Swanson (2008), Schmeling, Schrimpf, and Steffensen (2022) and Cieslak and Schrimpf (2019) estimate that risk premia in these short-term interest rate futures and monetary policy surprises are too small to explain the estimated degree of predictability in the data. Hence, Bauer and Swanson (2023) operate under the assumption that markets do not fulfill FIRE. Cieslak and Schrimpf (2019) and Schmeling, Schrimpf, and Steffensen (2022) also show that markets do not have full information about the Fed's reaction function before the trade, leading to the predictability of high-frequency monetary policy surprises ex post. We, therefore, use inflation compensation as a proxy measure for inflation expectations without explicitly taking into account the role of risk premia.

3.4.2 Monetary Policy

We identify monetary policy shocks using a high-frequency identification method. High-frequency identification controls for market expectations by considering changes in the target rate within a small window and, thus, overcomes two empirical challenges in identifying the effect of monetary policy. The first is that movements in the target rate exhibit both the independent effects of monetary policy and shifts in demand for risk-free assets because the Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect Fed's future actions because Fed officials could signal upcoming rate

[7] See Cochrane and Piazzesi (2005) and Lustig, Roussanov, and Verdelhan (2014).

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 changes over the 1-day windows from January 1, 1999, to June 30, 2019, in the following five interest rates: Federal funds rates futures for the current month, 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 quoted price on the contract and y_t is the implied yield to maturity. Second, we difference all variables across a window around FOMC announcements.

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

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

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

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

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

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

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

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

We collect these eight asset price responses into $T \times n$ matrix X,[8] 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 Gürkaynak, Sack, and Swanson (2005), we present these data in terms of a factor model,

$$X = F\Lambda + v \tag{3.9}$$

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

To estimate the unobserved factors F, we extract the first three principal components of X and rotate them to interpret as (i) the surprise component of the change in the Federal funds rate at

[8] $T = 171$ because there are 171 FOMC meetings from January 1, 1999, to June 30, 2019. $n = 8$ because we use eight asset price changes.

each FOMC meeting, (ii) the surprise component of the change in forward guidance, and (iii) the surprise component of any LSAP announcements. We impose the following identifying assumptions on the orthonormal rotation matrix. First, changes in forward guidance have no effect on the current Federal funds rate. Second, changes in LSAPs have no effect on the current Federal funds rate. Third, the variance of the LSAP factor is minimized in the pre-ZLB period corresponding to the sample from January 1, 1999, to February 1, 2009.

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

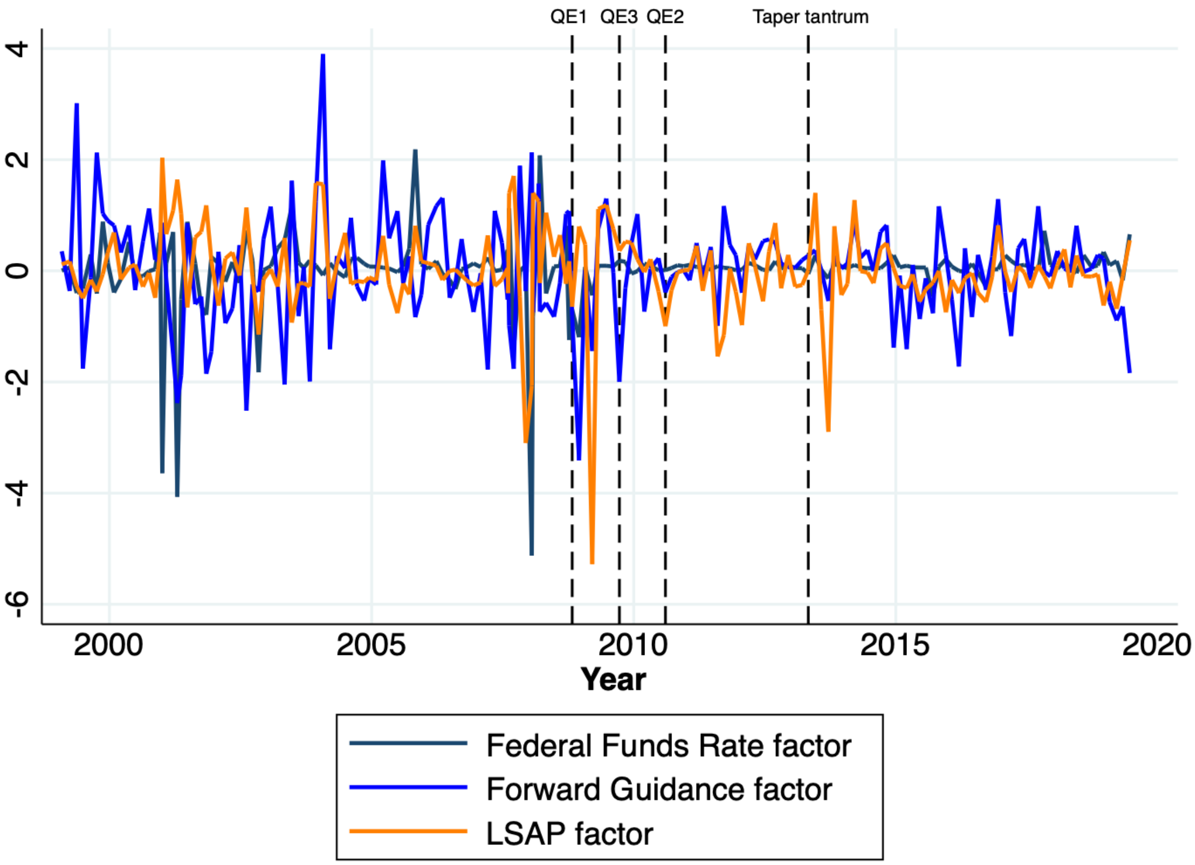
We plot the estimated Fed funds rate, forward guidance, and LSAP factors in Figure 3.1 and show how they line up with FOMC announcements that had significant implications for the LSAP factor. Events are QE1, the announcement of the original LSAP in November 2008; QE2, Bernanke's August 2010 speech suggesting an expansion of LSAPs; QE3, FOMC vote to buy $40b bonds per month in September 2012; Taper tantrum, Bernanke's 2013 FOMC press conference suggesting that FOMC would wind down purchases of mortgage-backed securities.

Table 3.2 reports the loading matrix implied by the identifying restrictions on the rotation matrix. Our results are broadly consistent with Swanson (2021) in signs[9] and the 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 11.4 basis points, the expected Federal funds rate at the next FOMC meeting by about 7.8 basis points, the second, third, and fourth Eurodollar futures rates by 4.0, 3.6,

[9] Note that we normalized shocks to correspond to monetary tightening - that is why the signs in the third row are opposite to those in Swanson (2021).

Figure 3.1: Estimated Fed Funds Rate, Forward Guidance, and LSAP Factors



The figure displays the estimated Fed funds rate, forward guidance, and LSAP factors from 1999 to 2019. Events are QE1, the announcement of the original LSAP in November 2008; QE2, Bernanke's August 2010 speech suggesting an expansion of LSAPs; QE3, FOMC vote to buy \$40b bonds per month in September 2012; Taper tantrum, Bernanke's 2013 FOMC press conference suggesting that FOMC would wind down purchases of mortgage-backed securities.

Table 3.2: Estimated Effects of Monetary Policy on Interest Rates, 1999–2019

	$mp1$	$mp2$	$ed2$	$ed3$	$ed4$	2Y Tr.	5Y Tr.	10Y Tr.
Fed Funds	11.38***	7.81***	4.00***	3.58***	2.83***	1.92***	1.19***	0.54***
	(0.19)	(0.17)	(0.13)	(0.06)	(0.12)	(0.14)	(0.08)	(0.10)
Forward	-0.00	1.23***	4.34***	5.57***	6.17***	4.79***	4.77***	3.39***
Guidance	(0.13)	(0.12)	(0.10)	(0.04)	(0.08)	(0.10)	(0.06)	(0.07)
LSAP	0.00	-1.41***	-1.64***	-1.06***	-0.34**	0.91***	2.85***	3.32***
	(0.17)	(0.15)	(0.12)	(0.06)	(0.10)	(0.13)	(0.07)	(0.09)
N	171	171	171	171	171	171	171	171
R^2_{adj}	0.96	0.93	0.95	0.99	0.97	0.93	0.98	0.96

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

The table provides 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.

and 2.8 basis points respectively, and the 2-, 5-, and 10-year Treasury yields by about 1.9, 1.2, and 0.5 basis points respectively. The effects of a surprise change in the Federal funds rate are largest at the short end of the yield curve and die off monotonically as the maturity of the interest rate increases, in line with the results from Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005).

The second row suggests that the effect of forward guidance on asset prices is hump-shaped peaking at approximately the one-year horizon and then diminishing at longer horizons, consistent with Gürkaynak, Sack, and Swanson (2005) and Campbell et al. (2012).[10]

The third row implies that a one standard deviation tightening in LSAP causes the 2-, 5- and 10-year treasury yields to rise on average.[11]

The estimates in this table are not only consistent with the literature but also suggest that the identified factors used in the shock construction correspond to changes in the Federal funds rate, forward guidance, and LSAPs.

[10] The effect of forward guidance on the current Federal funds rate is zero by construction.
[11] The effect of LSAP on the current Federal funds rate is zero by construction.

3.4.3 Expectations of Future Policy Rate

Since monetary policy in the U.S. is dominated by three components – Fed funds rate, forward guidance, and LSAP – we proxy expectations of the future policy rate at CPI release dates by three (rotated) principal components from changes in the 8 interest rates around CPI release dates. The rates we employ and identifying assumptions for factors are the same as the ones used for monetary policy shocks. Each of the principal components will correspond to the expectations about the Fed's action in terms of each policy instrument - Fed funds target, forward guidance, and LSAP. Figure 3.2 depicts the resulting series. Given that these factors identify market expectations about future policy rates, we can conclude that after the financial crisis, markets expected the Fed to operate through forward guidance and LSAP instruments.

3.4.4 Expectations of the Fed's Aggressiveness

We measure the expected Fed's reaction to inflation by the residuals from the regression given by[12]

$$\tilde{F}_{\tau}^{j} = \alpha_0 + \alpha_1 \Delta IC_{\tau,h} + \varepsilon_{\tau,h}^{j} \tag{3.10}$$

where τ indexes CPI announcement, $\tilde{F}^{j}$ denotes monetary policy component j (either the Fed funds rate, forward guidance, or LSAP), Δ is the daily change bracketing each CPI announcement, IC_h is the BEI over maturity h, and ε is the regression residual. As a result, we obtain three sets of residuals corresponding to three policy actions, estimated for 19 different maturities from 2 to 20 years. The residual from ε, identifies $\Delta\mathbb{E}_t\phi_{t,h} \times \mathbb{E}_t\pi_{t,h}$, so we define $\tilde{\varepsilon}_{\tau,h}^{j} = \frac{\hat{\varepsilon}_{\tau,h}^{j}}{IC_{\tau,h}}$ as a measure of changes in expectation about the Fed's aggressiveness.

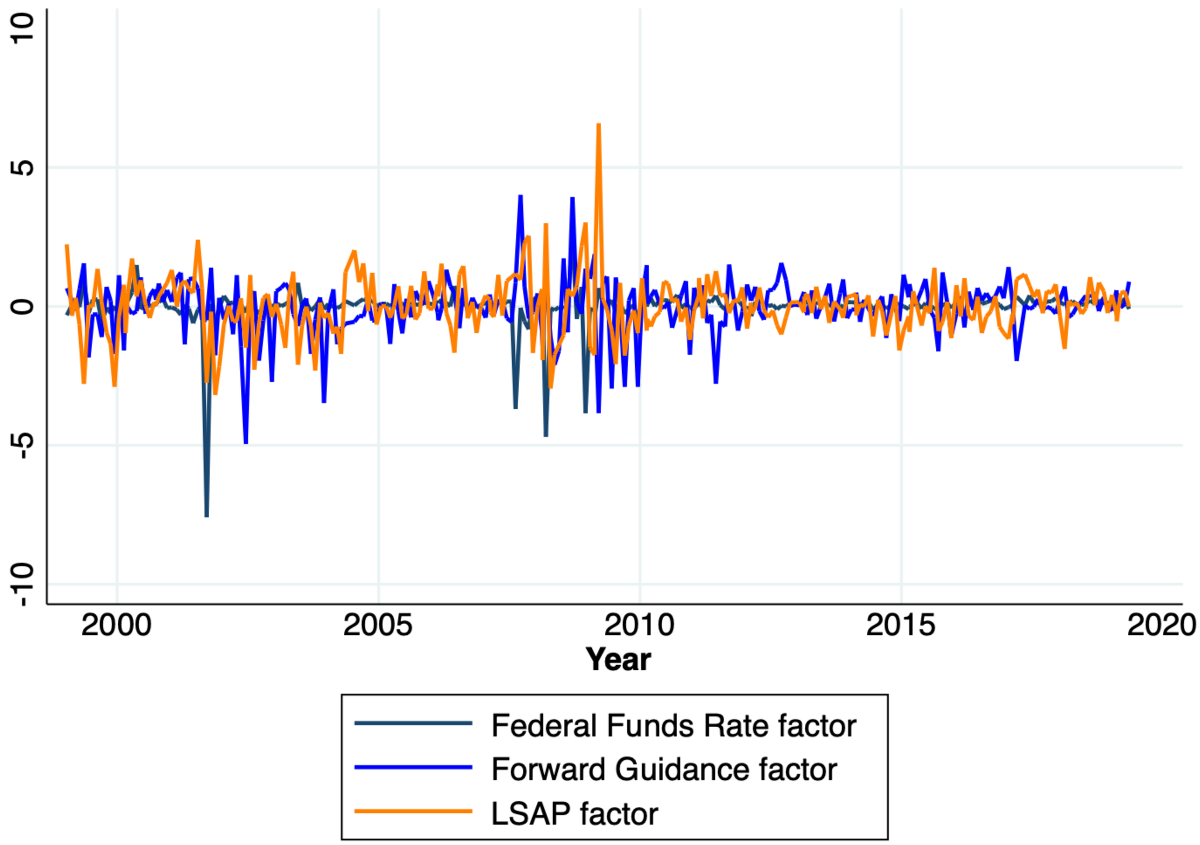
By construction, the mean of each residual $\hat{\varepsilon}$ from regression (3.10) around CPI releases is zero.[13] However, in our analysis we are going to use only residuals that precede FOMC announcements, resulting in 112 observations.[14]

[12]This regression is the counterpart of (3.3). The only difference is the notation - we substituted it to the estimated proxies for expectations obtained in the previous subsections.

[13]There were 187 CPI releases during our sample period from January 1, 2005, to June 30, 2019.

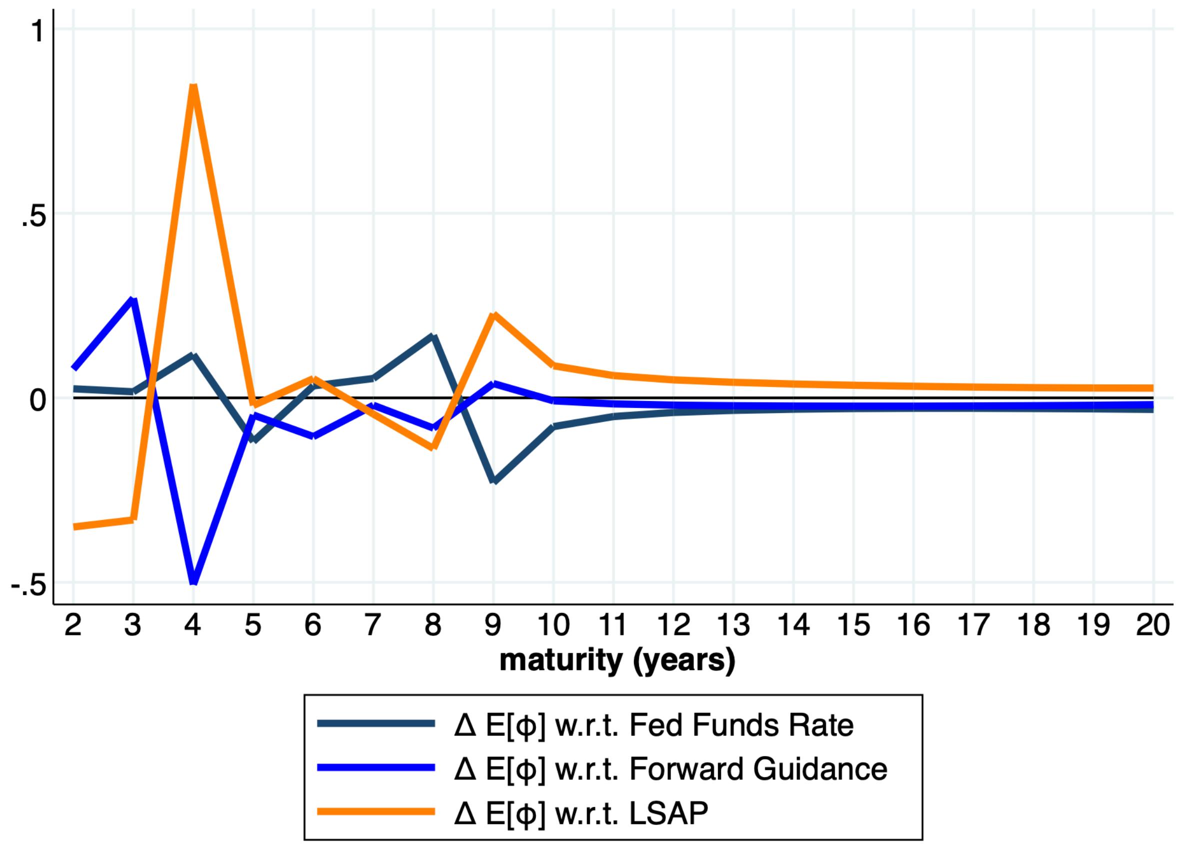
[14]All the empirical results that follow are based on these 112 FOMC announcements.

Figure 3.2: Estimated Fed Funds Rate, Forward Guidance, and LSAP Factors around CPI releases



The figure displays the estimated Fed funds rate, forward guidance, and LSAP factors from 1999 to 2019 around CPI releases. These factors measure expectations about future policy rates. See text for details.

Figure 3.3: Estimated Change in the Fed's Aggressiveness



The figure displays the average changes in expectation about the Fed's aggressiveness with respect to Fed funds rate, forward guidance, and LSAP factors for maturities from 2 to 20 years based on data from 2005 to 2019 for CPI releases that precede FOMC announcements. See text for details.

In Figure 3.3, we display the averages of $\tilde{\varepsilon}$ – the estimated changes in expectation about the Fed's aggressiveness with respect to Fed funds rate, forward guidance, and LSAP factors – for maturities from 2 to 20 years. Two observations stand out. The first is that the average estimates of the change in the Fed's aggressiveness starting from maturity of 10 years onward are very similar to those at longer maturities. This reflects strong co-movement between nominal and real interest rates at longer maturities. The second is that, due to negative inflation compensation observations, on average, for maturities from 10 to 20 years, the markets expect the Fed to lower its aggressiveness through the Fed funds rate and forward guidance and increase it through LSAP.

3.5 Empirical Results

In this section, we use market-based measures of expectations constructed in the previous section to study the relationship between inflation expectations and monetary policy. Our analysis comprises three steps. First, we document that our identified monetary shocks have a significant effect on nominal interest rates. Second, we provide evidence that real rates respond to forward guidance and LSAP shocks much stronger than nominal rates. Therefore, inflation compensation responds systematically to monetary policy shocks corresponding to forward guidance and LSAPs. Finally, we show that the response of inflation compensation to monetary policy is lower when markets expect the Fed's reaction to inflation to be more aggressive. In other words, the interaction between monetary policy and market expectations about Fed's aggressiveness has an opposite effect on inflation compensation to that of monetary policy.

3.5.1 The Effect of Monetary Policy on Nominal Interest Rates

In this subsection, we estimate the effects of the Fed funds rate, forward guidance, and LSAP on the nominal interest rates derived from U.S. Treasury yields.

Each column of Table 3.3 provides estimates from an OLS regression of the form

$$\Delta i_{t,h} = \alpha + \tilde{F}_t' \beta + u_t \tag{3.11}$$

where t indexes FOMC announcements, $i_{t,h}$ denotes nominal yields at a given maturity h, $\tilde{F}$ denotes the monetary policy factors, and Δ is the daily change bracketing each FOMC announcement, and u is a regression residual. The coefficients are in units of basis points per standard deviation surprise in each monetary policy component.

Figure 3.4 plots the results of these regressions for the effects of the Federal funds rate tightening (top panel), the effects of forward guidance tightening (middle panel), and the effects of LSAP tightening (bottom panel) on nominal interest rates for maturities from 2 to 20 years. The solid blue line in each panel plots the point estimates β as a function of maturity h, and the shaded grey

Table 3.3: Estimated Effects of Monetary Policy on U.S. Treasury Yields

Nominal Yield	2Y	5Y	10Y	20Y
Fed Funds	5.343***	3.258***	0.964	-0.164
	(0.673)	(0.847)	(0.901)	(0.838)
Forward Guidance	3.982***	4.316***	2.965***	1.006
	(0.497)	(0.625)	(0.664)	(0.618)
LSAP	3.305***	6.251***	6.404***	4.265***
	(0.498)	(0.627)	(0.667)	(0.620)
constant	-0.023	0.064	0.191	0.583
	(0.426)	(0.536)	(0.570)	(0.530)
N	112	112	112	112
R^2_{adj}	0.64	0.63	0.54	0.32

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

Coefficients β from regression (3.11). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

area contains ±1.96-standard-error bands around those estimates.

The first row of Table 3.3 and the top panel of Figure 3.4 suggest that a one standard deviation increase in the Federal funds rate causes the 2-year Treasury yields to rise about 5.3 basis points, with effects on longer-term yields that decrease monotonically with maturity, becoming statistically insignificant at maturity of 8 years.

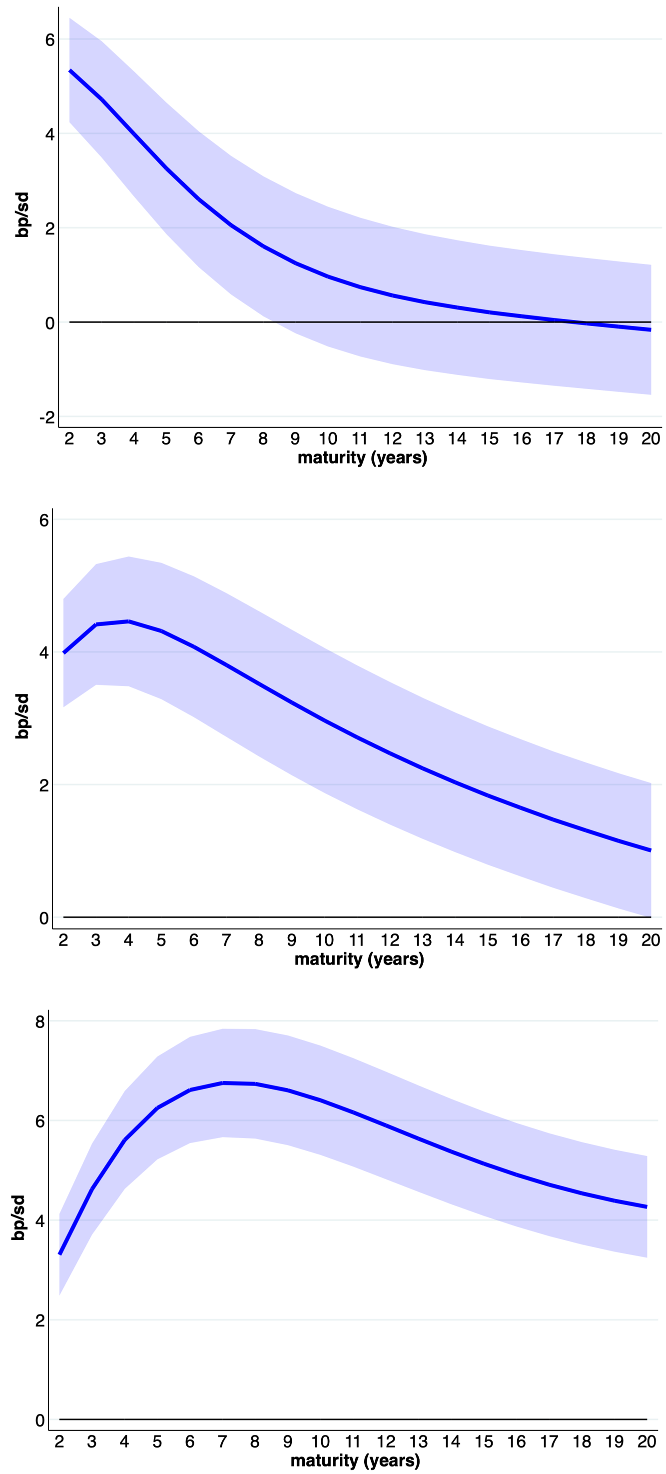
The second row of Table 3.3 and the middle panel of Figure 3.4 show that a one standard deviation increase in forward guidance has a hump-shaped effect on the yields curve, with a peak at the 4-year maturity.

The third row of Table 3.3 and the bottom panel of Figure 3.4 imply that a one standard deviation tightening in LSAP is also hump-shaped, peaking at the maturity of 7 years.

3.5.2 The Effect of Monetary Policy on Real Interest Rates and Inflation Compensation

Having established that our identified shocks have a similar effect on nominal yields as documented in Swanson (2021), in this subsection, we turn to the effect of monetary policy on real

Figure 3.4: Estimated Effects of Federal Funds (top panel), Forward Guidance (middle panel), and LSAP (bottom panel) Tightening on Nominal Interest Rates



Estimated coefficients $\hat{\beta}$ (solid blue line) and ±1.96-standard-error bands (shaded area) are from regression (3.11) for maturities from 2 to 20 years. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

Table 3.4: Estimated Effects of Monetary Policy on U.S. TIPS Yields

TIPS Yield	2Y	5Y	10Y	20Y
Fed Funds	4.778***	2.536**	1.244	0.747
	(1.308)	(1.063)	(0.966)	(0.846)
Forward Guidance	7.381***	6.389***	4.590***	2.852***
	(0.965)	(0.784)	(0.712)	(0.624)
LSAP	5.504***	6.719***	6.358***	4.075***
	(0.968)	(0.787)	(0.715)	(0.627)
constant	-0.749	-0.516	-0.355	-0.433
	(0.828)	(0.673)	(0.611)	(0.535)
N	112	112	112	112
R^2_{adj}	0.51	0.60	0.56	0.39

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

Coefficients β from regression (3.12). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

interest rates and inflation compensation.

We start by estimating the effect of monetary policy on real interest rates measured by the TIPS yields. Each column of Table 3.4 provides estimates from an OLS regression of the form

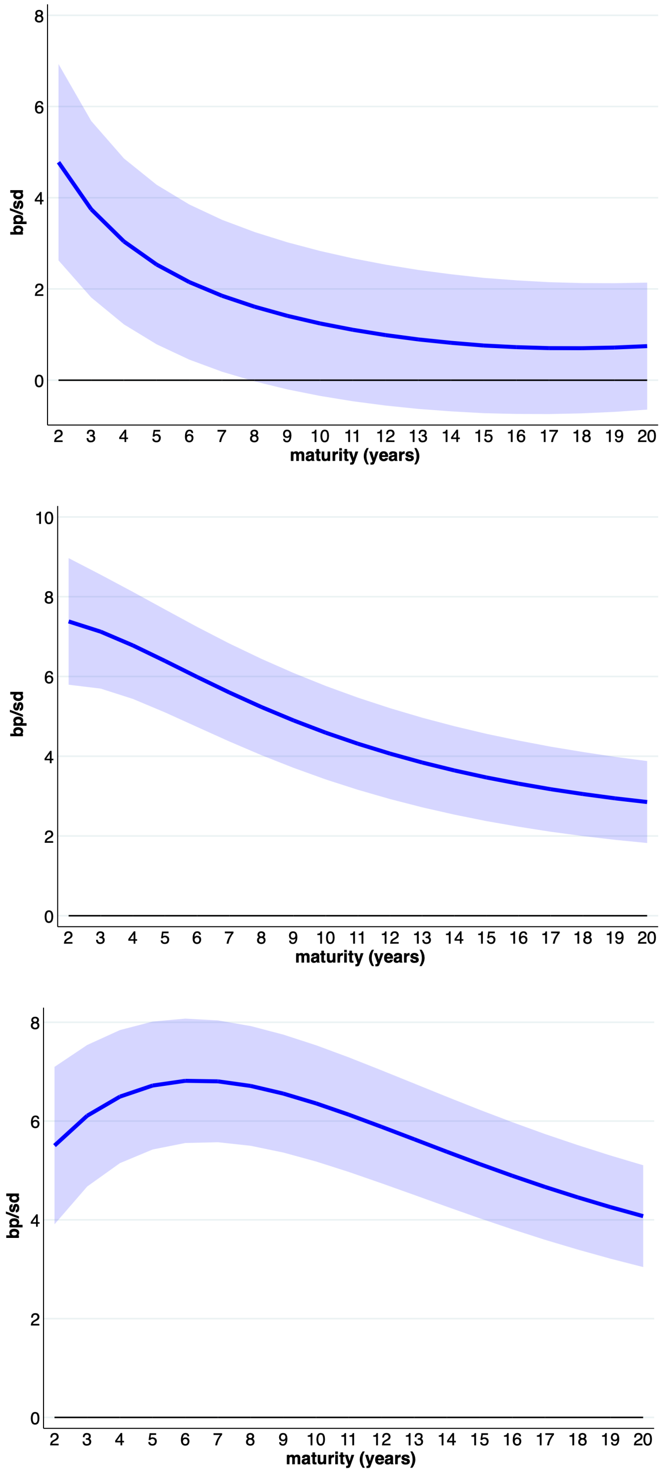
$$\Delta r_{t,h} = \alpha + \tilde{F}_t'\beta + u_t \tag{3.12}$$

where t indexes FOMC announcements, $r_{t,h}$ denotes TIPS yields at a given maturity h, $\tilde{F}$ denotes the monetary policy factors, Δ is the daily change bracketing each FOMC announcement, and u is a regression residual.

Figure 3.5 plots the results of these regressions for the effects of the Federal funds rate tightening (top panel), the effects of forward guidance tightening (middle panel), and the effects of LSAP tightening (bottom panel) on real yields for maturities from 2 to 20 years. The solid blue line in each panel plots the point estimates β as a function of maturity h, and the shaded grey area contains ± 1.96-standard-error bands around those estimates.

Table 3.4 and Figure 3.5 suggest that real yields respond to an increase in the Federal funds

Figure 3.5: Estimated Effects of Federal Funds (top panel), Forward Guidance (middle panel), and LSAP (bottom panel) Tightening on Real Yields



Estimated coefficients $\hat{\beta}$ (solid blue line) and $\pm$1.96-standard-error bands (shaded area) are from regression (3.12) for maturities from 2 to 20 years. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

Table 3.5: Estimated Effects of Monetary Policy on U.S. Inflation Compensation

Inflation Compensation	2Y	5Y	10Y	20Y
Fed Funds	0.565	0.723	-0.280	-0.911*
	(1.047)	(0.621)	(0.513)	(0.548)
Forward Guidance	-3.398***	-2.073***	-1.624***	-1.846***
	(0.772)	(0.458)	(0.378)	(0.404)
LSAP	-2.199***	-0.468	0.046	0.190
	(0.775)	(0.460)	(0.379)	(0.406)
constant	0.726	0.581	0.546*	1.015***
	(0.662)	(0.393)	(0.324)	(0.347)
N	112	112	112	112
R^2_{adj}	0.20	0.16	0.12	0.15

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

Coefficients β from regression (4.14). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

rate slightly less than nominal yields. Meanwhile, the response of real yields to a forward guidance shock is much stronger than that of nominal yields. For the LSAP shock, real yields respond more than nominal yields at shorter maturities but at longer maturities, the effects on real and nominal yields are somewhat similar.

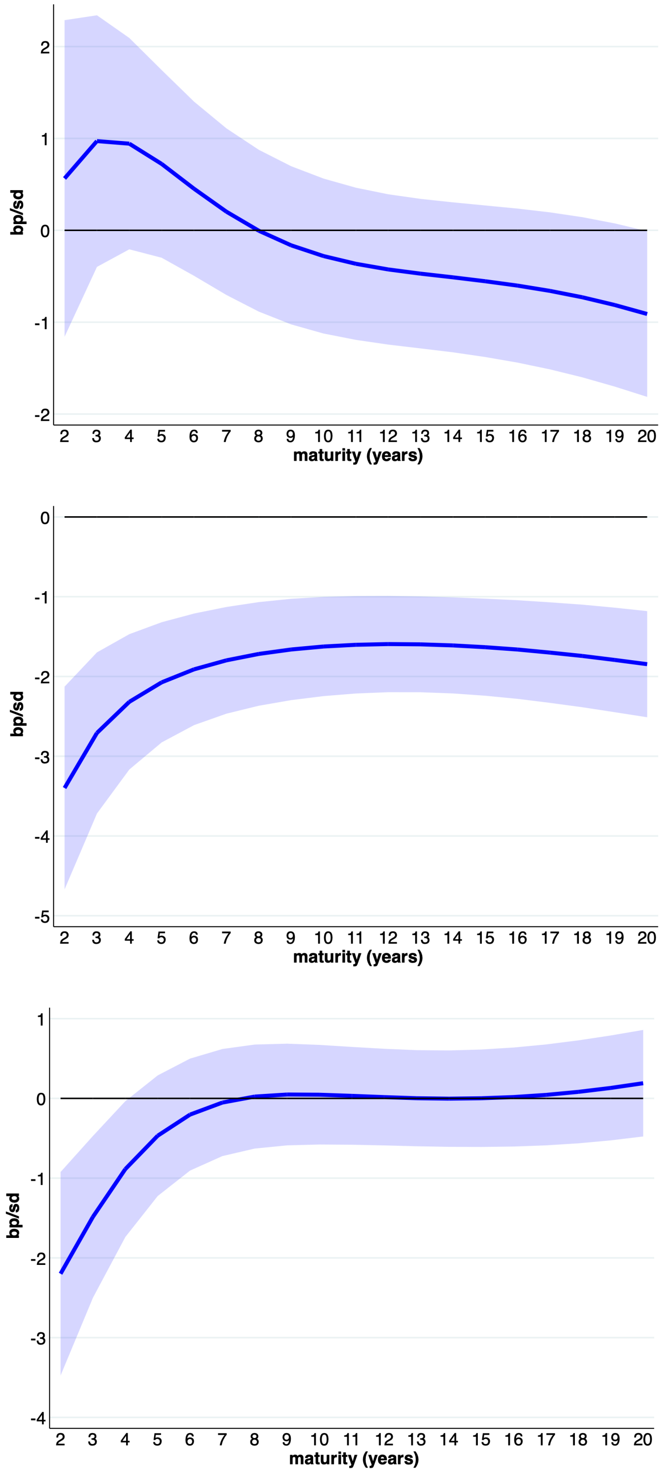
The combined evidence of monetary policy effects on nominal and real yields suggests that inflation will not respond to the shocks in the Fed funds rate, but will respond to shocks in forward guidance at all maturities, and to shocks in LSAP at short maturities. Our conjecture is readily verified by Table 3.5 and Figure 3.6 that display estimates from an OLS regression of the form

$$\Delta IC_{t,h} = \alpha + \tilde{F}_t' \beta + u_t \tag{3.13}$$

where t indexes FOMC announcements, $IC_{t,h}$ denotes inflation compensation over a given maturity h, $\tilde{F}$ denotes the monetary policy factors, and Δ is the daily change bracketing each FOMC announcement.

The first row of Table 3.5 and the top panel of Figure 3.6 show that a one-standard-deviation

Figure 3.6: Estimated Effects of Federal Funds (top panel), Forward Guidance (middle panel), and LSAP (bottom panel) Tightening on Inflation Compensation



Estimated coefficients $\hat{\beta}$ (solid blue line) and ±1.96-standard-error bands (shaded area) are from regression (4.14) for maturities from 2 to 20 years. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

increase in the Federal funds has essentially no effect on the inflation compensation.

The second row of Table 3.5 and the middle panel of Figure 3.6 show that a one-standard-deviation increase in the forward guidance has a negative but diminishing effect on the inflation compensation. The response of the inflation compensation implied by two-year rates is strongest and statistically significant amounting to -3.4 basis points per standard deviation. It gradually levels off to about -1.9 basis points at the 20-year maturity. All coefficients are highly statistically significant. This evidence suggests that inflation compensation responds systematically to monetary policy shocks corresponding to changes in the forward guidance.

The third row of Table 3.5 and the bottom panel of Figure 3.6 show that a one-standard-deviation contraction in the LSAPs has a negative effect on the inflation compensation only at short maturities of 2 and 3 years. The response of the inflation compensation implied by two-year rates is -2.2 basis points per standard deviation. The response is not significant for maturities from 4 to 20 years.

The main result of this subsection is that inflation compensation responds systematically to monetary policy shocks corresponding to changes in the forward guidance across all maturities and LSAPs at short maturities. In the next subsection, we will explore if the expectations about the Fed's aggressiveness dampen inflation expectations' response to forward guidance (at all maturities) and LSAP (at short maturities).

3.5.3 The Effect of Monetary Policy on Inflation Compensation Conditional on the Expected Aggressiveness of the Fed

In this subsection, we examine the effect of monetary policy on inflation compensation conditional on the change in the expected aggressiveness of the Fed. We show that at long maturities, the interaction between the forward guidance instrument and changes in market expectations about the Fed's aggressiveness has an opposite effect to that of monetary policy on inflation compensation. That is, given that markets expect the Fed to be more (less) aggressive, they adjust inflation expectations less (more).

To explore the effects of monetary policy on inflation compensation conditional on the change in the expected aggressiveness of the Fed, we estimate the OLS regressions of the form

$$\Delta IC_t^m = \alpha + \sum_{j=1}^{3} \beta_j \tilde{F}_{j,t} + \sum_{j=1}^{3} \gamma_j \tilde{\varepsilon}_{j,\tau} + \sum_{j=1}^{3} \delta_j \tilde{F}_{j,t} \tilde{\varepsilon}_{j,\tau} + u_t \tag{3.14}$$

where t indexes FOMC announcements, τ indexes the last CPI announcement preceding FOMC announcement t, IC denotes inflation compensation at a particular maturity m, Δ the daily change bracketing each FOMC announcement, $\tilde{F}$ the monetary policy factors estimated above, $\tilde{\varepsilon}$ market expectations about Fed's aggressiveness given by an estimated residual from regression 3.10, $\tilde{F}\tilde{\varepsilon}$ an interaction between the monetary policy factors and market expectations about Fed's aggressiveness, and u a regression residual.

Even though by standard economic theory monetary policy tightening should lead to lower inflation (implying $\beta + \delta < 0$), the coefficient δ does not necessarily have to be positive for all maturities to counteract the effects of the monetary tightening. First, in the context of expected inflation anchoring we are primarily interested in the far-ahead expectations, beyond 10 years. This horizon is sufficiently far out so that movements in inflation compensations at these maturities are not attributable to transitory responses of the economy to a shock. Second, because the inflation compensation time series includes some negative observations, revisions in the expected Fed's aggressiveness can be negative. If so, a negative δ will imply anchoring.

From Table 3.5 and Figure 3.6 in the previous section, we saw that inflation compensation responds negatively only to forward guidance tightening at all maturities.[15] We also saw in Figure 3.3 that, on average, the estimated change in the Fed's aggressiveness through forward guidance was negative. Therefore, we expect coefficient δ corresponding to the interactions with forward guidance to be negative at longer maturities to counteract the effects of these shocks.

Table 3.6 reports the responses of inflation compensation at maturities of 2-, 5-, 10- and 20 years to changes in three monetary policy factors and their interactions with the corresponding

[15] We also saw that the inflation compensation responds negatively to LSAP tightening for maturities of 2 and 3 years, but these horizons are too short for standard economic models to return to steady state.

expectations about the Fed's aggressiveness over the sample from January 1, 2005, to March 20, 2019. As in Table 3.5, the coefficients in Table 3.6 are in units of basis points per standard deviation tightening surprise in each monetary policy instrument.

Figure 3.7 plots the estimated coefficients $\hat{\beta}$ and $\hat{\delta}$ from these regressions for the effects of the Federal funds rate tightening (top panel), the effects of forward guidance tightening (middle panel), and the effects of LSAP tightening (bottom panel) on inflation compensation for maturities from 2 to 20 years. The solid blue line in each panel plots the point estimates β for each maturity, and the shaded blue area contains ±1.96-standard-error bands around those estimates. The solid orange line in each panel plots the point estimates δ for each maturity, and the shaded orange area contains ±1.96-standard-error bands around those estimates.

Our conjecture about negative δ in front of the forward guidance interaction is verified by columns (4) and (5) of Table 3.6 and the middle panel of Figure 3.7: for maturities longer than 10 years, the interaction term is significant and negative. For maturities below 10 years, it is not significant.

The evidence in this section suggests that inflation expectations are anchored because their response to monetary policy is smaller than that if expectations are de-anchored. If during the CPI release before the FOMC meeting markets expected Fed to be more aggressive through forward guidance tightening, inflation compensation does not decrease as much. On the contrary, the expectation of the Fed's reaction through the Fed funds rate and LSAP formed during the CPI release does not matter for the markets since it is counteracted by the incoming news about the Fed's future policies.

3.6 Conclusion

In this chapter, we used daily bond yield data to show that the sensitivity of inflation expectations to forward guidance is lower if the Fed is expected to be more aggressive to inflation. Intuitively, the Fed announcement leading to a rate change that is higher than expected from an important news release about inflation indicates that the markets expect the Fed to react more ag-

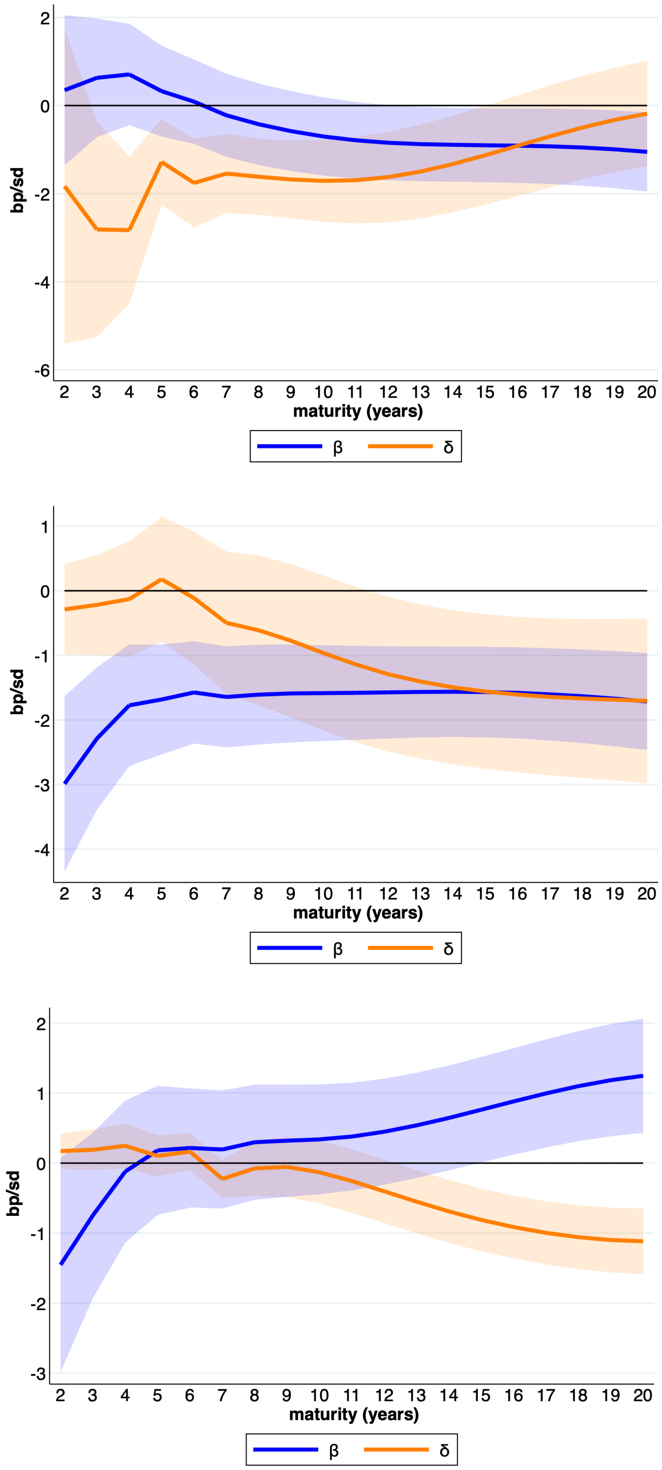
Table 3.6: Sensitivity of Inflation Compensation to Monetary Policy Conditional on the Expected Aggressiveness of the Fed

Inflation Compensation	2Y	5Y	10Y	15Y	20Y
Fed Funds	0.333	0.268	-0.750	-0.949*	-1.106**
	(1.039)	(0.633)	(0.537)	(0.510)	(0.546)
Forward Guidance	-3.021***	-1.792***	-1.656***	-1.621***	-1.774***
	(0.829)	(0.518)	(0.448)	(0.425)	(0.455)
LSAP	-1.459	0.167	0.380	0.810*	1.308***
	(0.934)	(0.564)	(0.474)	(0.457)	(0.496)
$\tilde{\varepsilon}_1$	-0.717	-1.692***	0.084	0.137	0.700
	(2.378)	(0.579)	(1.156)	(1.294)	(1.330)
$\tilde{\varepsilon}_2$	0.168	-0.156	-0.342	0.212	0.336
	(0.529)	(0.621)	(0.751)	(0.754)	(0.797)
$\tilde{\varepsilon}_3$	0.312	0.635	1.127	0.325	0.414
	(0.551)	(0.648)	(0.945)	(0.883)	(0.871)
$\tilde{F}_1 \times \hat{\varepsilon}_1$	-2.822	-1.214*	-1.812***	-1.213*	-0.260
	(2.176)	(0.621)	(0.564)	(0.681)	(0.723)
$\tilde{F}_2 \times \hat{\varepsilon}_2$	-0.306	-0.016	-1.060	-1.631**	-1.776**
	(0.426)	(0.598)	(0.723)	(0.725)	(0.773)
$\tilde{F}_3 \times \hat{\varepsilon}_3$	0.174	0.030	-0.050	-0.774***	-1.073***
	(0.154)	(0.162)	(0.272)	(0.272)	(0.283)
constant	0.820	0.512	0.604*	0.829***	0.988***
	(0.690)	(0.399)	(0.326)	(0.309)	(0.332)
N	112	112	112	112	112
R^2_{adj}	0.25	0.23	0.18	0.24	0.28

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

The table provides estimates of regression (4.15). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019.

Figure 3.7: Effects of Monetary Tightening Conditional on the Expected Fed's Aggressiveness



Estimated coefficients $\hat{\beta}$ (solid blue line) with ±1.96-standard-error bands (shaded blue area) and estimated coefficients $\hat{\delta}$ (solid orange line) with ±1.96-standard-error bands (shaded orange area) are from regression (4.15). The sample period is all regularly scheduled FOMC meetings from January 1, 2005, to June 30, 2019. See the text for details.

gressively in the future. If inflation expectations are anchored, markets will not adjust inflation expectations as much.

The main contribution of this chapter is to provide a market-based measure of the expected Fed's aggressiveness to inflation. We do this by extracting residuals from a regression of the changes in future policy rates on changes in inflation expectations.

Our main findings can be summarized as follows. First, we provide evidence suggesting that conventional monetary policy does not affect inflation compensation, whereas forward guidance tightening reduces inflation compensation, and LSAP tightening reduces inflation compensation at short horizons. Second, we show that the interaction between forward guidance and the expected Fed's aggressiveness at long maturities increases inflation compensation, partially counteracting the effect of the forward guidance tightening. Our findings are consistent with the anchoring of long-term inflation expectations.

Chapter 4: Anchoring of Inflation Expectations: Role of Inflation Risk

4.1 Introduction

The results of the previous chapter imply that the sensitivity of the TIPS inflation compensation to forward guidance is lower if the Fed is expected to be more aggressive to inflation.

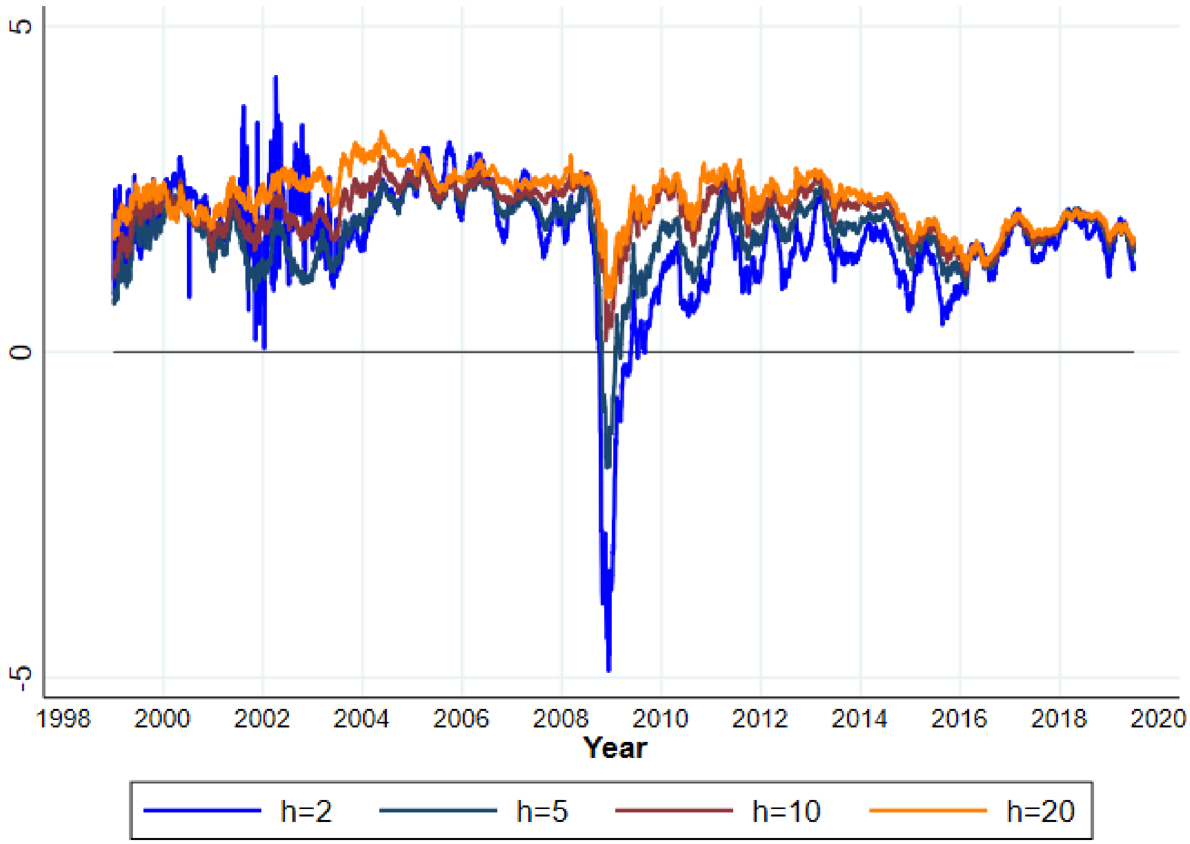
However, the TIPS inflation compensation is a noisy measure of inflation expectations for two reasons. The first is that any measure of inflation compensation includes inflation risk. By standard economic theory

$$i_{t,h} = r_{t,h} + \mathbb{E}_t \pi_{t,h} + IRP_{t,h} \tag{4.1}$$

where $i_{t,h}$ is the nominal interest rate for a bond of maturity h, $r_{t,h}$ is the real interest rate for a bond of the same maturity, $\mathbb{E}_t \pi_{t,h}$ is expected future inflation over h, and $IRP_{t,h}$ is an inflation risk premium. The latter measures the compensation that investors demand to cover the expected rate of future inflation and the risks associated with the uncertainty of future inflation at a given horizon and depends on the covariance between inflation and economic activity.

Accounting for the inflation risk premium can be crucial for analyzing inflation expectations. Campbell, Sunderam, and Viceira (2017) show that inflation risk premium was slightly positive on average from 1953 to 2014, being unusually high in the early 1980s when investors were more worried about stagflation scenarios with higher inflation accompanied by lower growth. It became negative in the early 21st Century, particularly in the downturns of 2001 and 2007 to 2009, as investors have become more concerned about outcomes where lower inflation is associated with lower growth. Figure 4.1 plots the inflation compensation time series for maturities of 2-, 5-, 10- and 20 years. In December 2008, the 2-year and 5-year inflation compensation measures fell below zero by around 5 and 2 percentage points. However, all series recovered most of their declines by the start of the second round of LSAPs in the fourth quarter of 2011. This fall in

Figure 4.1: Inflation Compensation Time Series



The Figure displays the TIPS inflation compensation for maturities of 2-, 5-, 10- and 20 years. The sample period is from January 1, 2003, to June 30, 2019.

inflation expectations after the start of the Financial Crisis is documented in the literature as the "low inflation puzzle under quantitative easing."[1]

The second reason why inflation compensation derived from TIPS yield is a noisy measure of inflation expectations in the liquidity risk. Even though the market for TIPS has grown substantially since its inception in 1997, the TIPS yield exceeds the true real interest rate due to the TIPS liquidity premium:

$$r_{t,h}^{TIPS} = r_{t,h} + LRP_{t,h}^{TIPS} \tag{4.2}$$

[1] See Wen (2013), Thorbecke (2017), Feldstein (2015), Arias and Wen (2014).

where $r_{t,h}^{TIPS}$ is the yield on TIPS, and $LRP_{t,h}^{TIPS}$ is the TIPS liquidity premium.

D'Amico, Kim, and Wei (2018) show that TIPS liquidity premium was as much as 100 basis points when TIPS was first launched, as it took some time for TIPS to gain popularity among investors. It again surged during the 2008–2009 Financial Crisis, as investors fled from less liquid or more risky instruments and sought the safety and liquidity of nominal Treasury securities. Apart from the lower liquidity of TIPS relative to nominal Treasuries, this premium may also reflect the supply-demand imbalance of TIPS versus nominal securities and a greater concentration of buy-and-hold investors in the TIPS market compared with the nominal Treasury market.

Consequently, TIPS inflation compensation or BEI can be written as

$$IC_{t,h}^{TIPS} = \mathbb{E}_t \pi_{t,h} + IRP_{t,h} - LRP_{t,h}^{TIPS} \tag{4.3}$$

which implies that BEI deviates from inflation expectations due to inflation risk premium, TIPS liquidity premium, or both.

In this chapter, I use the methodology developed in the previous chapter to test the anchoring of inflation expectations using three measures of inflation expectations derived from no-arbitrage term structure models. The first measure comes from D'Amico, Kim, and Wei (2018), DKW henceforth, who jointly model nominal Treasury yields, TIPS yields, and realized inflation to decompose TIPS inflation compensation into three components: inflation expectation, inflation risk premium, and TIPS liquidity premium. To construct the second measure, I use the approximation by Wu and Xia (2016), WX henceforth, to estimate a shadow rate structure model (SRTSM) for nominal yields, which is useful for risk premium extraction at zero lower bound. I decompose nominal yields into two components: expectations and the term premium and use the latter as a proxy for an inflation risk premium. The third measure is expected inflation from a five-factor Gaussian affine term structure model (GATSM) developed by Abrahams et al. (2016), ACM henceforth.

I obtain two main findings. First, I show that all these measures respond to monetary tightening differently. The DKW measure (somewhat surprisingly) responds positively to tightening shocks in all three instruments. The ACM measure responds positively to tightening through the Fed funds rate, whereas the WX measure does not respond to it. The responses of the ACM and WX to unconventional monetary policy are more consistent with intuition: both measures of inflation expectation decline in response to the rate increase. Second, I show that expectations about the Fed's aggressiveness do not affect the sensitivity of the DKW and the WX measures to monetary shocks. However, they dampen the responsiveness of the ACM inflation expectations to Fed funds and LSAP monetary shocks.

The conclusions about anchoring inflation expectations are very different once I adjust inflation compensation for risk premia. If inflation expectations derived from the ACM model are a reasonable approximation for the true inflation expectations, then evidence in this chapter implies that market expectations dampen changes in inflation expectations in response to monetary policy through Fed funds and LSAP channels.

The rest of this chapter is organized as follows. In section 4.2, I describe the construction of each of the three measures of inflation expectations. In section 4.3, I re-estimate the Fed's expected aggressiveness and examine the sensitivity of each proxy for inflation expectations to monetary policy, conditional on estimated aggressiveness. In section 4.4, I summarize the main results.

4.2 Measures of Inflation Expectations

All three measures of inflation expectations that I employ in this chapter are based on no-arbitrage pricing models which assume that

$$\mathbb{E}_t \left[M_{t+1} R^h_{t+1} \right] = 1 \tag{4.4}$$

where the scalar $M_{t+1} > 0$ is a kernel that prices all bonds and R^h_{t+1} is a one-period gross return on a bond of maturity h. That is

$$R^h_{t+1} = \frac{P^{h-1}_{t+1}}{P^h_t} \tag{4.5}$$

where P_t^h is the price of bond with maturity h at time t and $P_t^0 = 1$.[2]

I assume an essentially affine pricing kernel

$$-\log M_{t+1} = i_t + \frac{1}{2}\lambda_t'\lambda_t + \lambda_t'\epsilon_{t+1} \tag{4.6}$$

where i_t is the continuously compounded short-term nominal interest rate, λ_t is a $N \times 1$ vector of N underlying risk factors, and ϵ_{t+1} is a vector of innovations. The N risk factors summarize the state space and follow a first-order Gaussian VAR process under the physical measure $\mathbb{P}$:

$$X_t = \mu + \Phi X_{t-1} + \Sigma\epsilon_t \tag{4.7}$$

where $\epsilon \sim N(0, I_N)$. Risk prices and shadow rate s_t are assumed to be related to the N factors through affine mappings

$$\lambda_t = \lambda_0 + \lambda_1 X_t \tag{4.8}$$

$$s_t = \delta_0 + \delta_1' X_t \tag{4.9}$$

It can be shown that the dynamics of the factors under the risk-neutral pricing kernel $M_t = exp\{-i_t\}$ are also VAR(1):

$$X_t = \mu^{\mathbb{Q}} + \Phi^{\mathbb{Q}} X_{t-1} + \Sigma\epsilon_t \tag{4.10}$$

where $\mu^{\mathbb{Q}} = \mu - \lambda_0$ and $\Phi^{\mathbb{Q}} = \Phi - \lambda_1$. The VAR process (4.10) is referred to as the "$\mathbb{Q}$-measure."

DKW and ACM measures

D'Amico, Kim, and Wei (2018) and Abrahams et al. (2016) assume that $i_t = s_t$ which implies that yields are linear in state variables. Both papers estimate GATSMs that include pricing of the Treasury and TIPS yield curves. Their estimations differ in the pricing factors they employ and the way to account for liquidity premium.

D'Amico, Kim, and Wei (2018) estimate a GATSM for the joint pricing of the Treasury yields,

[2]A bond with maturity h at time t becomes a bond with maturity $h - 1$ at time $t + 1$.

TIPS yields, and realized inflation. They model TIPS liquidity premium as a latent factor.

Abrahams et al. (2016), on the other hand, construct an indicator of the TIPS liquidity and directly use it with other factors of the model – three principal components from the cross-section of Treasury yields and two principal components extracted from orthogonalized TIPS yields. They construct an index of TIPS liquidity by averaging two observable indicators. The first indicator is the average absolute TIPS yield curve fitting error from the Nelson-Siegel-Svensson model employed by Gürkaynak, Sack, and Wright (2010). The second indicator is the 13-week moving average of the ratio of primary dealers' nominal Treasury transaction volumes relative to TIPS transaction volumes.

In my analysis, I directly use expected inflation measures provided by DKW and ACM.

The DKW dataset is available for download on the Board of Governors' website.[3] It provides daily data on expected and risk components of 5- and 10-year nominal yields and inflation compensation.

The ACM dataset is available for download on the Federal Reserve Bank of New York website.[4] It provides daily data on the term premium of nominal yields with maturities from 1 to 10 years.

WX measure

Wu and Xia (2016) argue that GATSMs are not suitable for studying the expected rate component at zero lower bound because they do not impose non-negativity restrictions and can predict negative rates. They enforce the lower bound on the observed short-term interest rate by allowing the observed rate to be equal to the corresponding shadow short rate only if the latter is above the lower bound, and a lower bound $\underline{r}$ otherwise:

$$i_t = \max\{s_t, \underline{r}\} \tag{4.11}$$

[3] Available at `https://www.federalreserve.gov/econres/notes/feds-notes/DKW-updates.csv`.

[4] Available at `https://www.newyorkfed.org/research/data_indicators`.

This assumption implies that yields are nonlinear in state variables and do not have analytical expressions. Wu and Xia (2016) show that under assumptions (4.6)–(4.9) and (4.11), the time t one period forward rate for a loan starting at $t+n$ and maturing at $t+n+1$, $f_{n,n+1,t}$, is approximately equal to

$$f_{n,n+1,t} = \underline{r} + \sigma_n^{\mathbb{Q}} g\left(\frac{a_n + b_n' X_t - \underline{r}}{\sigma_n^{\mathbb{Q}}}\right) \tag{4.12}$$

where $(\sigma_n^{\mathbb{Q}})^2 \equiv Var_t^{\mathbb{Q}}(s_{t+n})$.

I use this approximation to estimate monthly expected and risk components of nominal treasury yields from Gürkaynak, Sack, and Wright (2010) dataset using the extended Kalman filter. After obtaining the monthly measure of the term premium, I calculate the daily term premium by assuming it is constant over a month. I use the latter as a proxy for the daily inflation risk premium.

It is important to note that even though the nominal yield premium is a reasonable proxy for the inflation risk premium, it does not account for the liquidity premium. Therefore, the results using this measure of inflation expectations should be interpreted with caution.

4.3 Empirical Results

As in the previous section, I proceed in three steps. First, I construct the expected Fed's aggressiveness for each of the measures of inflation expectations described in the previous section. Then I show that all these measures respond negatively to forward guidance tightening and LSAP tightening. The DKW measure responds positively to Fed funds tightening only at short maturity, the ACM measure responds positively to it at all maturities, whereas the WX measure does not respond to it at any maturity. Finally, I explore the sensitivity of these measures to monetary shocks conditional on the Fed's aggressiveness. I show that expectations about the Fed's aggressiveness do not affect the sensitivity of the DKW and the WX measures to monetary shocks. However, they dampen the responsiveness of the ACM inflation expectations to Fed funds and LSAP monetary shocks.

4.3.1 Expectations of the Fed's Aggressiveness

I measure the expected Fed's reaction to inflation by the residuals from the regression given by

$$\tilde{F}^j_\tau = \alpha_0 + \alpha_1 \Delta\pi^e_{\tau,h} + \varepsilon^j_{\tau,h} \tag{4.13}$$

where τ indexes CPI announcement, $\tilde{F}^j$ denotes monetary policy component j (either the Fed funds rate, forward guidance, or LSAP), Δ is the daily change bracketing each CPI announcement, π^e_h is one of the three measures of inflation expectations described above over maturity h, and ε is the regression residual.

4.3.2 The Effect of Monetary Policy Inflation Expectations

I estimate an OLS regression of the form

$$\Delta IC_{t,h} = \alpha + \tilde{F}'_t\beta + u_t \tag{4.14}$$

where t indexes FOMC announcements, $IC_{t,h}$ denotes inflation compensation over a given maturity h, $\tilde{F}$ denotes the monetary policy factors, and Δ is the daily change bracketing each FOMC announcement.

Table 4.1 provides OLS estimates for the regression (4.14) using the DKW measure of inflation expectations. Interestingly, monetary tightening increases this measure of inflation expectations. A one standard deviation increase in the Fed funds factor, corresponding to monetary tightening, increases inflation expectations over a horizon of 5 years by 0.6 basis points. This effect is only marginally significant (10% significance level) for a horizon of 10 years. Shocks in both forward guidance and LSAP factor significantly increase inflation expectations over horizons of 5 and 10 years.

Table 4.2 and Figure 4.2 provide estimates for the regression (4.14) using the ACM measure of inflation expectations. They suggest that inflation expectations increase in response to Fed funds

Table 4.1: Estimated Effects of Monetary Policy on U.S. Inflation Compensation (DKW measure)

Inflation Expectations	5Y	10Y
Fed Funds	0.608^{**}	0.444^{*}
	(0.306)	(0.264)
Forward Guidance	0.771^{***}	0.584^{***}
	(0.136)	(0.118)
LSAP	1.391^{***}	1.183^{***}
	(0.155)	(0.133)
constant	-0.038	-0.034
	(0.130)	(0.112)
N	129	129
R^2_{adj}	0.52	0.49

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

Coefficients β from regression (4.14). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

shock but decrease in response to forward guidance and LSAP shocks. The effects of the Fed funds and LSAP shocks remain significant over all maturities from 2 to 10 years, but those of forward guidance dissipate starting from the maturity of 7 years.

Table 4.3 and Figure 4.3 provide estimates for the regression (4.14) using the WX measure of inflation expectations. They suggest that inflation expectations do not respond to the Fed funds shock and decrease in response to forward guidance and LSAP shocks, consistent with intuition. The effects of unconventional monetary policies remain highly significant over all maturities from 2 to 10 years.

Table 4.2: Estimated Effects of Monetary Policy on U.S. Inflation Compensation (ACM measure)

Inflation Expectations	2Y	5Y	10Y
Fed Funds	2.383**	3.345***	3.239***
	(1.139)	(0.920)	(0.916)
Forward Guidance	-2.313***	-1.365**	-0.661
	(0.723)	(0.584)	(0.581)
LSAP	-3.037***	-3.938***	-3.857***
	(0.830)	(0.670)	(0.667)
constant	0.424	0.183	0.178
	(0.688)	(0.556)	(0.554)
N	130	130	130
R^2_{adj}	0.18	0.28	0.24

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

Coefficients β from regression (4.14). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

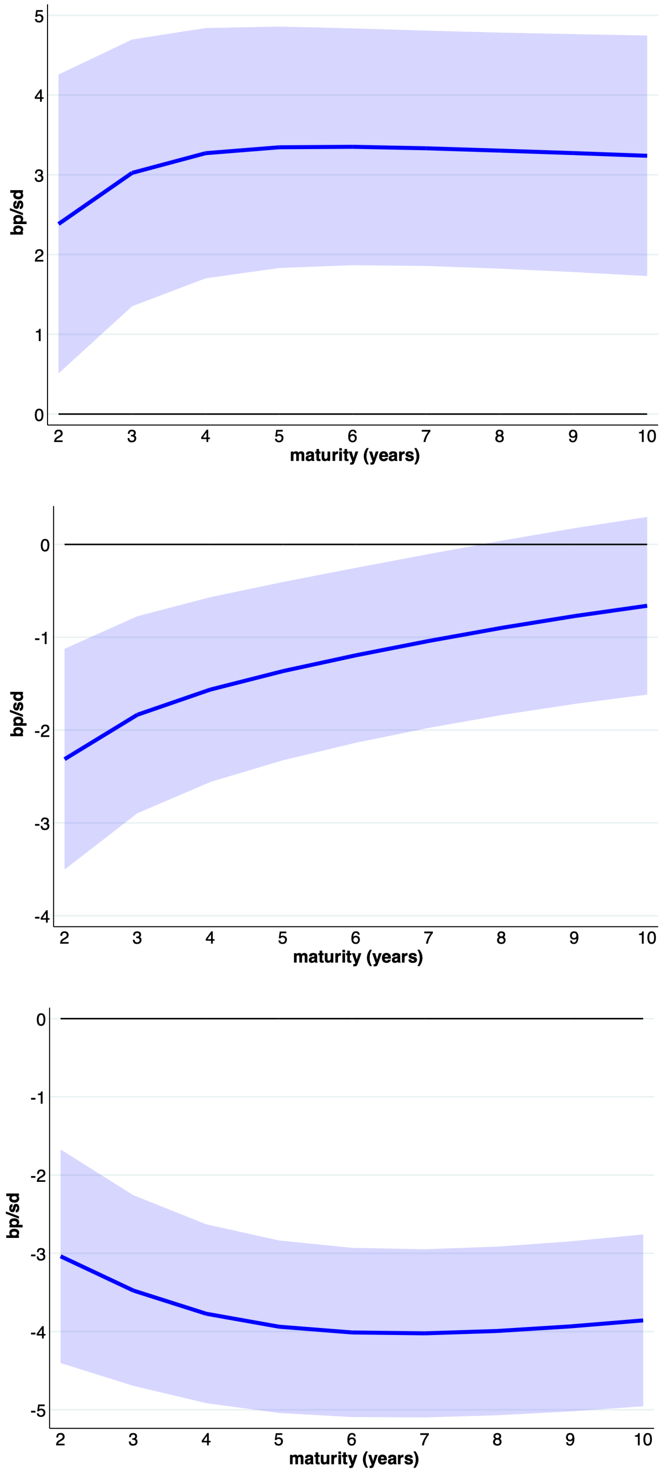
Table 4.3: Estimated Effects of Monetary Policy on U.S. Inflation Compensation (WX measure)

Inflation Expectations	2Y	5Y	10Y	15Y	20Y
Fed Funds	-0.353	-0.367	-0.541	-0.490	-0.648
	(1.345)	(1.059)	(0.816)	(0.728)	(0.676)
Forward Guidance	-3.717***	-3.472***	-2.813***	-2.319***	-2.074***
	(0.865)	(0.681)	(0.525)	(0.468)	(0.435)
LSAP	-4.306***	-4.856***	-3.854***	-3.062***	-2.386***
	(0.981)	(0.772)	(0.595)	(0.531)	(0.493)
constant	1.057	0.541	0.351	0.460	0.527
	(0.815)	(0.642)	(0.494)	(0.441)	(0.410)
N	129	129	129	129	129
R^2_{adj}	0.25	0.37	0.39	0.34	0.30

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

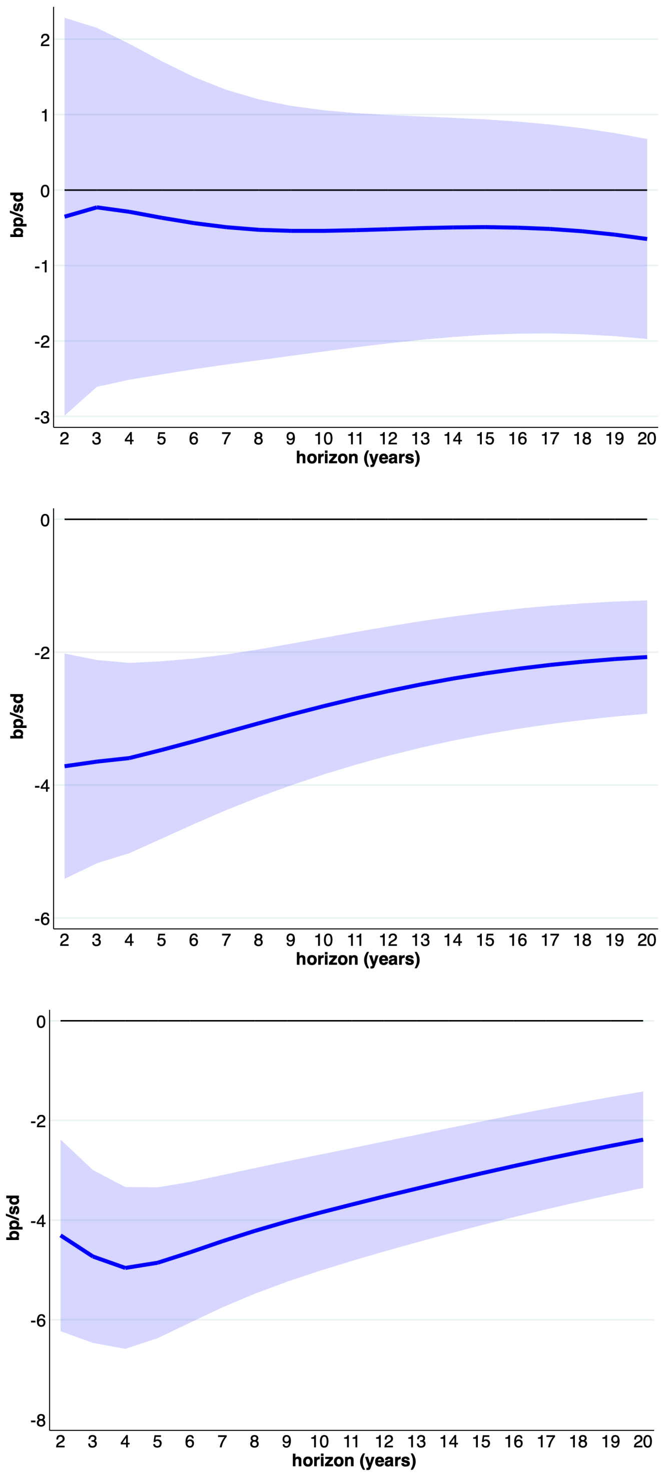
Coefficients β from regression (4.14). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

Figure 4.2: Estimated Effects of Federal Funds (top panel), Forward Guidance (middle panel), and LSAP (bottom panel) Tightening on Inflation Expectations (ACM measure)



Estimated coefficients $\hat{\beta}$ (solid blue line) and ±1.96-standard-error bands (shaded area) are from regression (4.14) for maturities from 2 to 20 years. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

Figure 4.3: Estimated Effects of Federal Funds (top panel), Forward Guidance (middle panel), and LSAP (bottom panel) Tightening on Inflation Expectations (WX measure)



Estimated coefficients $\hat{\beta}$ (solid blue line) and ± 1.96-standard-error bands (shaded area) are from regression (4.14) for maturities from 2 to 20 years. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

4.3.3 The Effect of Monetary Policy on Inflation Compensation Conditional on the Expected Aggressiveness of the Fed

To explore the effects of monetary policy on inflation compensation conditional on the change in the expected aggressiveness of the Fed, I estimate the OLS regressions of the form

$$\Delta\pi_t^e = \alpha + \sum_{j=1}^{3}\beta_j\tilde{F}_{j,t} + \sum_{j=1}^{3}\gamma_j\tilde{\varepsilon}_{j,\tau} + \sum_{j=1}^{3}\delta_j\tilde{F}_{j,t}\tilde{\varepsilon}_{j,\tau} + u_t \tag{4.15}$$

where t indexes FOMC announcements, τ indexes the last CPI announcement preceding FOMC announcement t, π^e denotes a measure of inflation expectations at a particular maturity m, Δ the daily change bracketing each FOMC announcement, $\tilde{F}$ the monetary policy factors estimated above, $\tilde{\varepsilon}$ market expectations about Fed's aggressiveness given by an estimated residual from regression 4.13, $\tilde{F}\tilde{\varepsilon}$ an interaction between the monetary policy factors and market expectations about Fed's aggressiveness, and u a regression residual.

Since expected inflation numbers are positive for all three measures, the data will be consistent with long-term inflation expectation anchoring if the coefficient δ has the opposite sign to that of β.

Table 4.4 provides estimation results of regression 4.15 using the DKW measure of inflation expectations. With the inclusion of the expected Fed's aggressiveness, the coefficient in front of the Fed funds factor became insignificant. However, that for forward guidance and LSAP remains positive and highly significant. The interaction terms do not affect the inflation expectations response to monetary policy.

Table 4.5 and Figure 4.4 provide estimation results of regression (4.15) using the ACM measure of inflation expectations. The coefficients in front of interaction terms of the Fed's aggressiveness with the Fed funds rate and that with the LSAP factor are highly significant. Moreover, they have the opposite sign to the corresponding $\hat{\beta}$-s, implying that expectations about the Fed's aggressiveness dampen changes in inflation compensation when a monetary shock hits. The coefficient in front of the interaction term of the Fed's aggressiveness with forward guidance is insignificant.

Table 4.4: Sensitivity of Inflation Compensation to Monetary Policy Conditional on the Expected Aggressiveness of the Fed (DKW measure)

Inflation Expectations	5Y	10Y
Fed Funds	0.377	0.331
	(0.358)	(0.312)
Forward Guidance	0.670^{***}	0.501^{***}
	(0.156)	(0.136)
LSAP	1.453^{***}	1.292^{***}
	(0.165)	(0.142)
$\tilde{\varepsilon}_1$	0.093	0.126
	(0.750)	(0.692)
$\tilde{\varepsilon}_2$	-0.429	-0.396
	(0.493)	(0.408)
$\tilde{\varepsilon}_3$	1.614^{*}	1.221^{*}
	(0.962)	(0.573)
$\tilde{F}_1 \times \hat{\varepsilon}_1$	-0.433	-0.257
	(0.469)	(0.430)
$\tilde{F}_2 \times \hat{\varepsilon}_2$	0.252	0.289
	(0.320)	(0.296)
$\tilde{F}_3 \times \hat{\varepsilon}_3$	-0.945	-0.538
	(0.646)	(0.573)
constant	-0.010	-0.018
	(0.129)	(0.113)
N	127	127
R^2_{adj}	0.55	0.52

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

The table provides estimates of regression (4.15). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

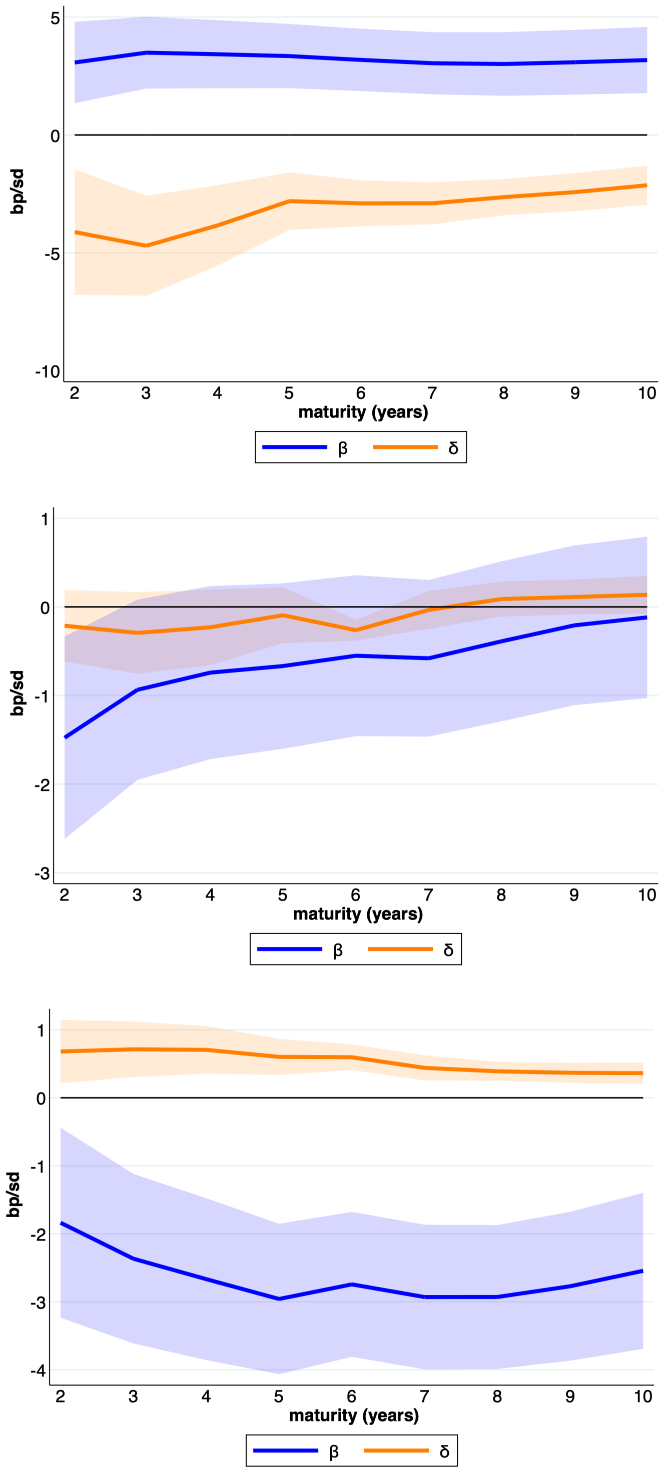
Table 4.5: Sensitivity of Inflation Compensation to Monetary Policy Conditional on the Expected Aggressiveness of the Fed (ACM measure)

Inflation Expectations	2Y	5Y	10Y
Fed Funds	3.116***	3.358***	3.177***
	(1.051)	(0.826)	(0.848)
Forward Guidance	-1.466**	-0.664	-0.068
	(0.696)	(0.566)	(0.550)
LSAP	-1.880**	-2.947***	-2.554***
	(0.850)	(0.670)	(0.689)
$\tilde{\varepsilon}_1$	6.189***	2.794***	1.539***
	(1.587)	(0.841)	(0.524)
$\tilde{\varepsilon}_2$	-0.786*	-0.572***	-0.082
	(0.406)	(0.135)	(0.130)
$\tilde{\varepsilon}_3$	-1.247**	-0.172	-0.256*
	(0.617)	(0.233)	(0.142)
$\tilde{F}_1 \times \hat{\varepsilon}_1$	-4.177**	-2.846***	-2.137***
	(1.610)	(0.736)	(0.492)
$\tilde{F}_2 \times \hat{\varepsilon}_2$	-0.216	-0.085	0.106
	(0.258)	(0.191)	(0.121)
$\tilde{F}_3 \times \hat{\varepsilon}_3$	0.693**	0.612***	0.347***
	(0.289)	(0.162)	(0.094)
constant	0.207	-0.156	-0.312
	(0.639)	(0.516)	(0.505)
N	128	128	128
R^2_{adj}	0.34	0.43	0.42

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

The table provides estimates of regression (4.15). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

Figure 4.4: Effects of Monetary Tightening Conditional on the Expected Fed's Aggressiveness (ACM measure)



Estimated coefficients $\hat{\beta}$ (solid blue line) with ±1.96-standard-error bands (shaded blue area) and estimated coefficients $\hat{\delta}$ (solid orange line) with ±1.96-standard-error bands (shaded orange area) are from regression (4.15). The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019. See the text for details.

Table 4.6 and Figure 4.5 provide estimation results of regression (4.15) using the WX measure of inflation expectations. The coefficients in front of interaction terms of the Fed's aggressiveness with the forward guidance factor and that with the LSAP factor have the opposite sign to the corresponding $\hat{\beta}$-s but are insignificant. The coefficient in front of the interaction term of the Fed's aggressiveness with the Fed funds factor is insignificant.

4.4 Conclusion

In this chapter, I use the methodology developed in the previous chapter to test the anchoring of inflation expectations using three measures of inflation expectations derived from no-arbitrage term structure models.

I obtain two main findings. First, I show that all these measures respond to monetary tightening differently. The DKW measure responds positively to tightening shocks in all three instruments. The ACM measure responds positively to tightening through the Fed funds rate, whereas the WX measure does not respond to it. The responses of the ACM and WX to unconventional monetary policy are more consistent with intuition: both measures of inflation expectation decline in response to the rate increase. Second, I show that expectations about the Fed's aggressiveness do not affect the sensitivity of the DKW and the WX measures to monetary shocks. However, they dampen the responsiveness of the ACM inflation expectations to Fed funds and LSAP monetary shocks.

Out of the three measures used above the ACM is the most reliable. Inflation expectations implied by the DKW model respond positively to monetary tightening, which is not consistent with standard macroeconomic models. The inflation expectation measure that I constructed following the WX approach does not account for the liquidity premium.

If inflation expectations derived from the ACM model are a reasonable approximation for the true inflation expectations, then evidence in this chapter implies that market expectations dampen changes in inflation expectations in response to monetary policy through Fed funds and LSAP.

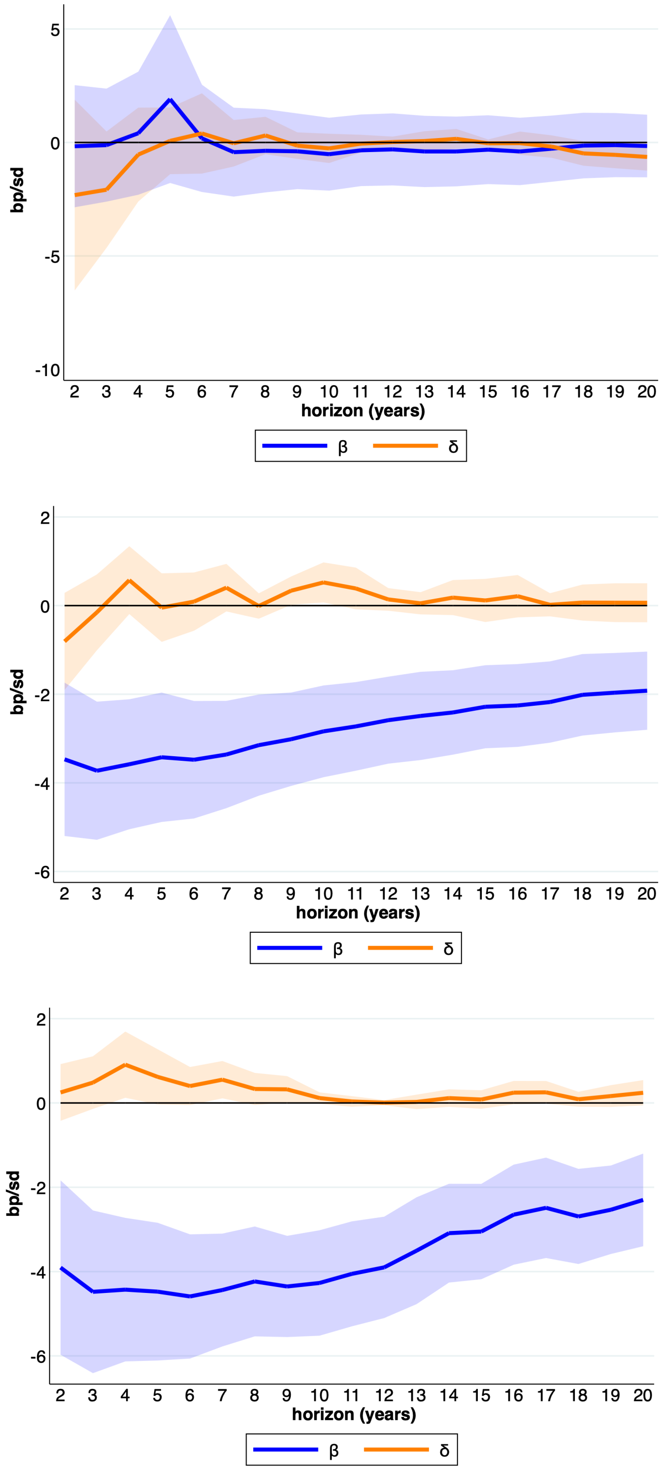
Table 4.6: Sensitivity of Inflation Compensation to Monetary Policy Conditional on the Expected Aggressiveness of the Fed (WX measure)

Inflation Expectations	2Y	5Y	10Y	15Y	20Y
Federal Funds	-0.166	1.910	-0.517	-0.318	-0.157
	(1.372)	(1.885)	(0.819)	(0.773)	(0.704)
Forward Guidance	-3.470***	-3.423***	-2.838***	-2.283***	-1.921***
	(0.883)	(0.745)	(0.528)	(0.478)	(0.450)
LSAP	-3.904***	-4.476***	-4.270***	-3.050***	-2.300***
	(1.055)	(0.833)	(0.638)	(0.577)	(0.560)
$\tilde{\varepsilon}_1$	4.085**	0.949	0.281	0.008	0.682
	(2.056)	(0.966)	(0.390)	(0.081)	(0.527)
$\tilde{\varepsilon}_2$	-0.192	-0.427	0.167*	0.084	0.030
	(0.421)	(0.432)	(0.098)	(0.177)	(0.179)
$\tilde{\varepsilon}_3$	-0.6	-0.031	-0.052	0.026	-0.051
	(0.590)	(0.135)	(0.150)	(0.052)	(0.197)
$\tilde{F}_1 \times \hat{\varepsilon}_1$	-2.319	0.07	-0.261	-0.036	-0.637**
	(2.142)	(0.748)	(0.329)	(0.086)	(0.307)
$\tilde{F}_2 \times \hat{\varepsilon}_2$	-0.808	-0.046	0.523**	0.116	0.064
	(0.558)	(0.395)	(0.23)	(0.248)	(0.225)
$\tilde{F}_3 \times \hat{\varepsilon}_3$	0.249	0.619*	0.116*	0.082	0.241
	(0.343)	(0.333)	(0.069)	(0.112)	(0.153)
constant	0.647	0.400	0.199	0.460	0.378
	(0.845)	(0.657)	(0.499)	(0.441)	(0.413)
N	128	128	128	129	128
R^2_{adj}	0.26	0.37	0.41	0.34	0.32

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

The table provides estimates of regression (4.15). Coefficients are in units of basis points per standard deviation change in the monetary policy instruments. The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019.

Figure 4.5: Effects of Monetary Tightening Conditional on the Expected Fed's Aggressiveness (WX measure)



Estimated coefficients $\hat{\beta}$ (solid blue line) with $\pm$1.96-standard-error bands (shaded blue area) and estimated coefficients $\hat{\delta}$ (solid orange line) with $\pm$1.96-standard-error bands (shaded orange area) are from regression (4.15). The sample period is all regularly scheduled FOMC meetings from January 1, 2003, to June 30, 2019. See the text for details.

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Appendix A: Appendix to Chapter 1

A.1 Mortgage Sample Representativeness

We treat our sample as representative of the population - Figure A.1 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.

A.2 Additional Empirical Results

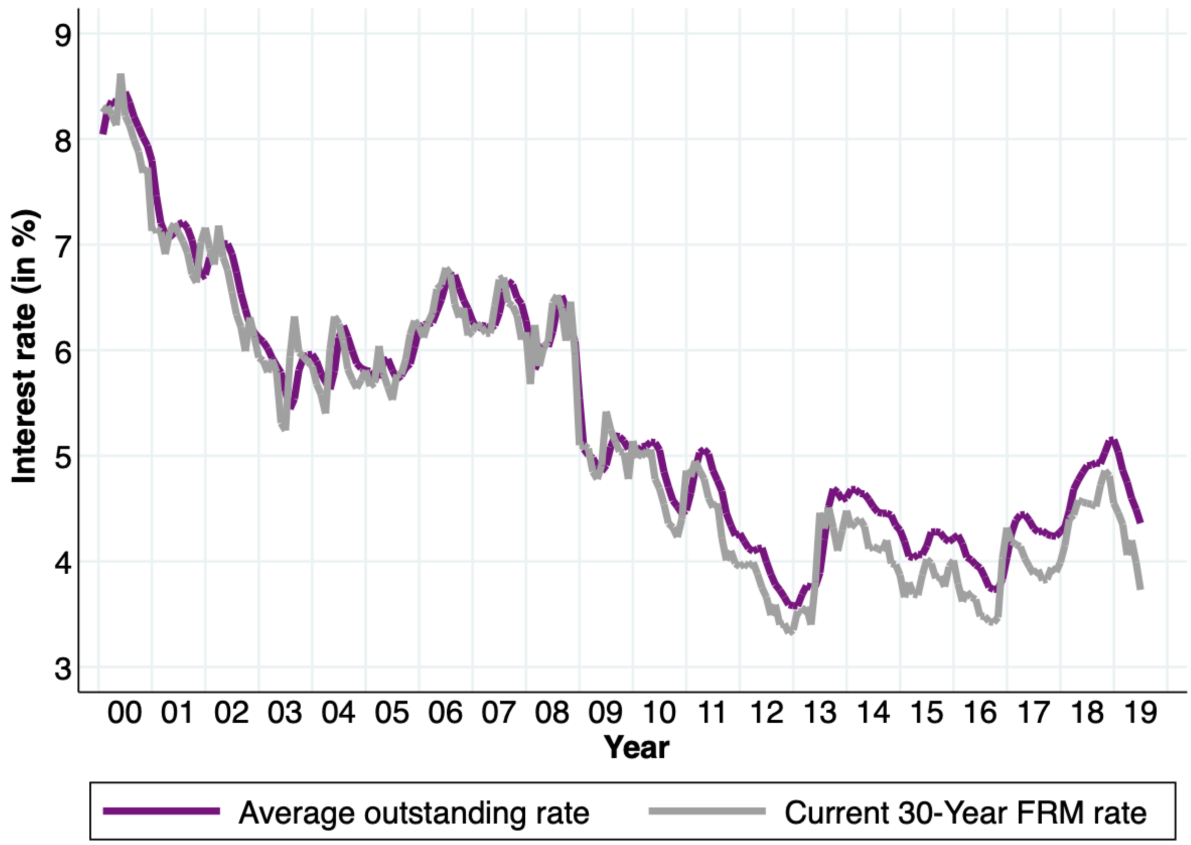
Figure A.2 is the quarterly version of Figure 1.7 in the main text. The key difference between Figure 1.7 is that the interest rate gaps and refinance indicators are averaged quarterly (as opposed to monthly). A comparison between Figure 1.7 and Figure A.2 shows that they are very similar. In particular, both show significant differences in refinancing between lower and upper-quartile credit score borrowers.

Figure A.3 is the annualized version of Figure 1.7 in the main text. The key difference between Figure 1.7 is that the interest rate gaps and refinance indicators 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 increasingly imprecise.

A.3 Construction of Monetary Policy Shocks

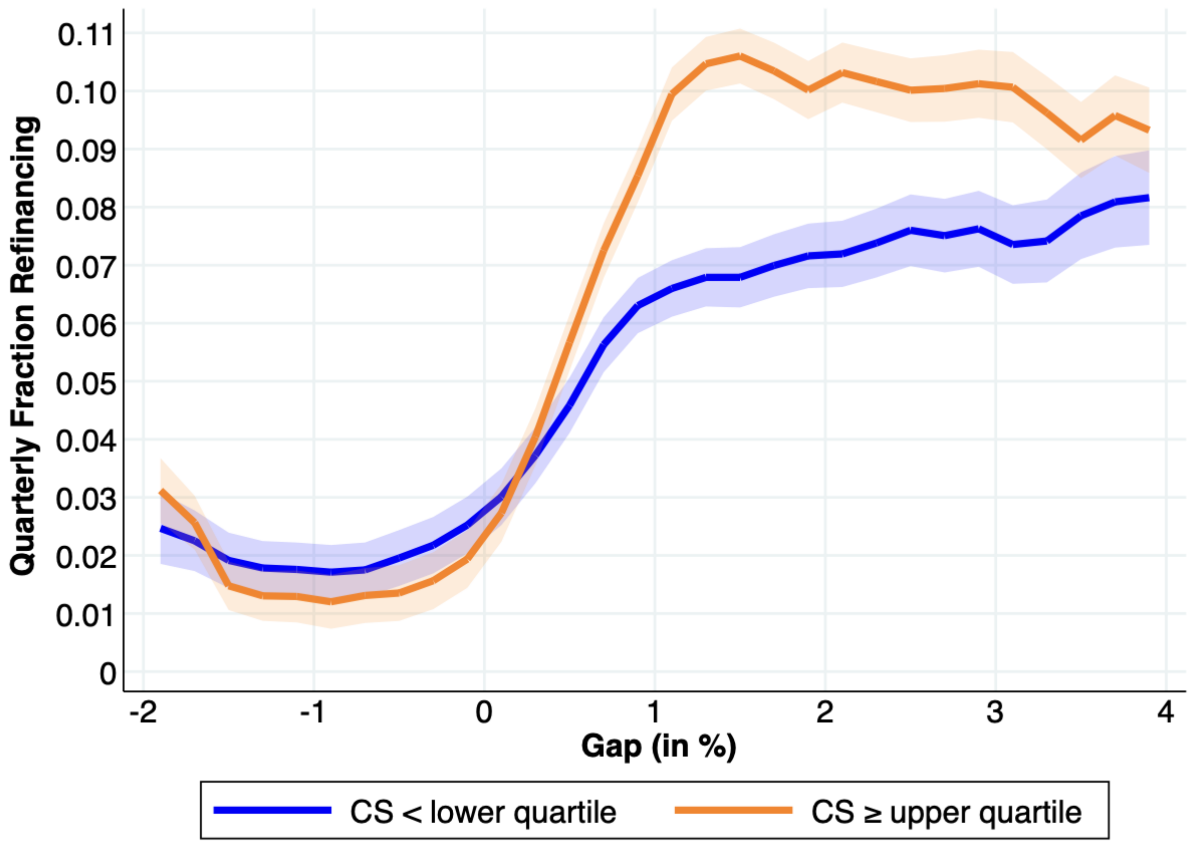
We use high-frequency measures of monetary policy shock. High-frequency identification controls the market expectations by considering changes in the target rate within a small window and, thus, overcomes two empirical challenges in identifying the effect of monetary policy. The first is that movements in the target rate exhibit both the independent effects of monetary policy

Figure A.1: Average Outstanding Rate in Fannie Mae Data vs. Market Mortgage Rate (FRED)



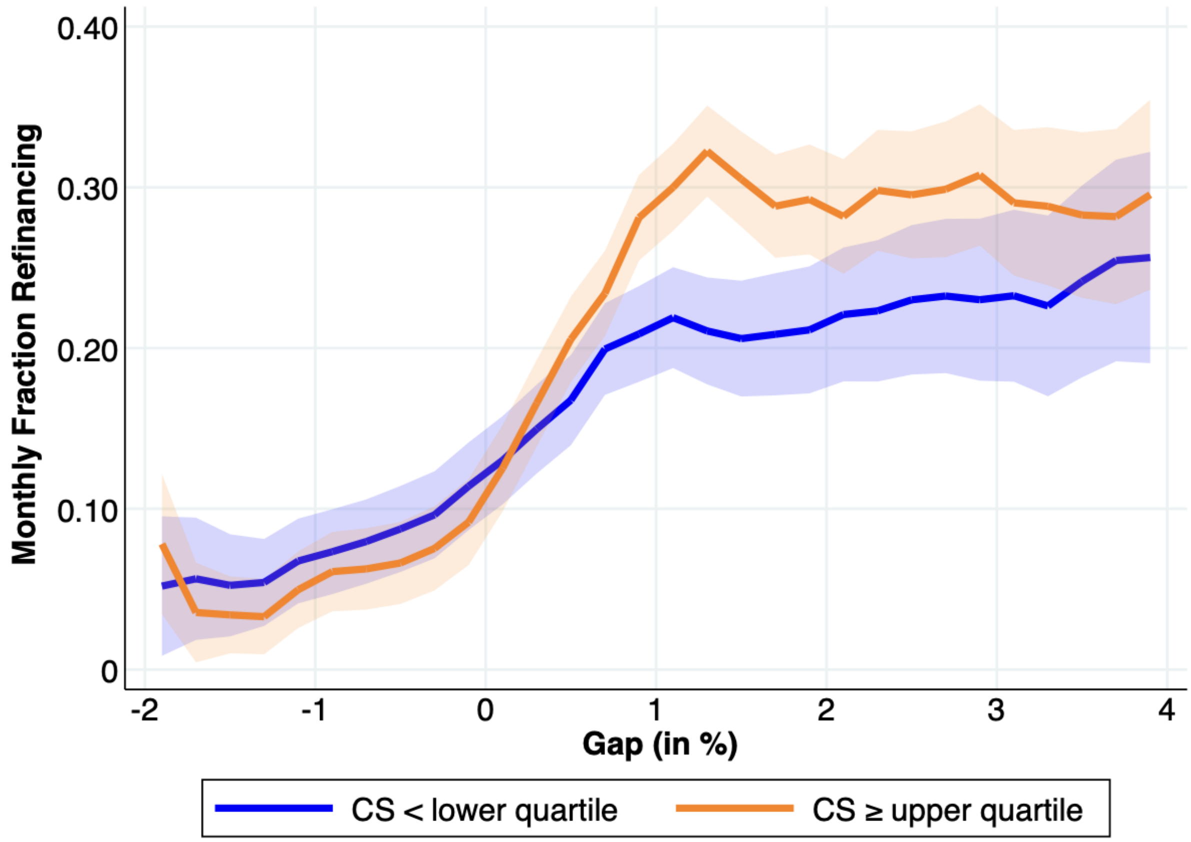
The figure shows the average outstanding mortgage rate of the Fannie-Mae Single-Family Loan-Level historical data and the market mortgage rate from FRED, Federal Reserve Bank of St. Louis at `https://fred.stlouisfed.org/series/MORTGAGE30US`.

Figure A.2: Robustness of Refinance Hazard to Quarterly Frequency for Lower and Upper Quartile Credit Score Borrowers



The figure shows point estimates for coefficients $\beta + \gamma + \delta$ on the 20bp bin dummies in regression (1.2) 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 A.3: Robustness of Refinance Hazard to Annual Frequency for Lower and Upper Quartile Credit Score Borrowers



The figure shows point estimates for coefficients $\beta + \gamma + \delta$ on the 20bp bin dummies in regression (1.2) 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.

and shifts in demand for risk-free assets because the Fed conducts policy endogenously in response to economic events that affect interest rates in the economy. The second is that markets may expect 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 quoted price on the contract and y_t is the implied yield to maturity. Second, we difference all variables across a window around FOMC announcements.

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

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

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

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

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

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

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

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

We collect these eight asset price responses into $T \times n$[1] 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,

$$X = F\Lambda + v \tag{A.1}$$

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

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

and across assets.

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

We perform two normalizations of the rotated factors. First, the sign of the first rotated column is such that it has a positive effect on the current federal funds rate, the second factor has a positive effect on the four-quarter-ahead Eurodollar future contract ED4, and the third factor has a negative effect on the 10-year Treasury yield. This way an increase in the first two factors corresponds to a monetary tightening, whereas an increase in the third factor corresponds to an easing.[2] 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 A.1 reports the loading matrix implied by the identifying restrictions on the rotation matrix. Our results are broadly consistent with Swanson (2021) in signs and magnitude of coefficients although we use daily rate data and employ a shorter sample to identify monetary policy shocks.

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

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

Table A.1: Structural Loading Matrix

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

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

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.

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 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 corresponds pretty to changes in the federal funds rate, forward guidance, and LSAPs.