Unconventional Monetary Policy Transmission and Bank Market Power

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Abstract

I investigate how unconventional monetary policy affects the mortgage market through the bank market power channel. Empirically, I find that for unconventional monetary policy shocks, such as an increase in 10-year Treasury yield by 3.85 basis points (bps), high market power banks transmit 0.15 to 0.69 bps less to mortgage rates relative to low market power banks. In contrast, high market power FinTech lenders pass-through 2 to 3.36 bp more relative to their low market power counterparts. Monetary policy transmission is higher at higher rates before 2009 zero lower bound (ZLB), and it is higher at lower rates during ZLB periods.

JEL Codes: E44, E52, G21

Keywords: Bank market power, mortgages, unconventional monetary policy

1 Introduction

FinTech lenders have gained a larger share of the mortgage market after the financial crisis, and less is known about their role in transmitting monetary policy shocks. Financial institutions play important roles when transmitting monetary policy shocks to mortgage rates, which substantially impact household liquidity. The Federal Reserve has been responding to the financial crisis by cutting interest rates to historically low levels and by embarking on a series of unconventional policy actions. Although extensive literature has already investigated the impact of traditional interest rate movements on real activity and inflation (Bernanke, Gertler, and Gilchrist (1999), Tenreyro and Thwaites (2016), Christiano, Eichenbaum, and Evans (2005)), little is known about the role of financial institutions and pass-through of unconventional monetary policies on mortgage rates.

In this paper, I investigate how unconventional monetary policy affects the mortgage market through the bank market power channel in traditional banks and FinTech lenders. I find that, in response to a 3.85 basis points (bps) increase in 10-year Treasury yield, high market power banks transmit monetary policy shocks by 0.15 to 0.69 bps less to mortgage rates, whereas high market power FinTech lenders pass-through 2 to 3.36 bps more relative to their low market power counterparts.

FinTech lenders transmit monetary policy shocks more to mortgage rates due to their relatively expensive funding from investors even though they do not face any regulatory costs. High market power traditional banks transmit less because they are incentivized to hold mortgages when policy rates are lower as they pay high operating costs on deposits that are insensitive to policy rates.

I then use Jordà (2005)'s local projection method to understand how monetary policy shocks evolve over time and check asymmetric responses between conventional and unconventional monetary policy changes. Pass-through of monetary shocks to mortgage rates is higher at higher policy rates and monetary policy transmission to mortgage rates is higher at lower policy rates during ZLB. Market concentration amplifies monetary policy transmission during ZLB, but dampens the pass-through in pre-ZLB periods. Although ZLB reduces banks' net interest margins, high market power banks need to hold long-term fixed assets in order to pay their deposit franchises. This transmits less of the monetary policy shocks to mortgage rates, because deposits are insensitive to interest rates.

Further, I use quantile regression to test if highly concentrated banks transmit monetary policy differently through their distribution of mortgage rates. High market power banks transmit 1.5 bps less on lower quantiles of mortgage rates in contrast to 0.2 bps less on higher quantiles of mortgage rate relative to low market power banks. In order to entice borrowers, high market power banks transmit less in the bottom distribution relative to low market power banks. High market power banks also charge lower rates in the bottom distribution of mortgage rates, as borrowers are price sensitive and less willing to pay a premium, as they could easily switch to FinTech lenders.

High market power FinTech lenders pass-through 2 to 4 bps more, uniformly across its quantiles of mortgage rates. FinTech lenders rely on mortgage securitization and investors for mortgage funding and transmit more monetary policy due to their expensive sources of funding. Although FinTech lenders do not face any regulatory costs, they face higher funding sources resulting in net higher transmission.

This paper mainly contributes to the body of literature on the monetary policy transmission to the mortgage market through traditional banks and FinTech lenders. First, it contributes to the literature of competition between traditional banks and FinTech lenders. Using novel shadow bank funding data, Jiang, Matvos, Piskorski, and Seru (2020) finds that shadow bank debt obtain their funding from their competitors. Jiang (2019) investigates that traditional banks have market power in the upstream market for shadow banks' funding, which in turn softens competition in the downstream mortgage origination market. Buchak, Matvos, Piskorski, and Seru (2018) discovers that shorter time-to-sale of FinTech lenders provide them with a competitive advantage in mortgage lending and directly affect competition in the mortgage market. Fuster, Plosser, Schnabl, and Vickery (2019) studies how technology affects mortgage lending after the crisis and affects frictions in the mortgage origination process, such as slow processing times, capacity constraints, and slow or suboptimal refinancing. Their findings suggest that technology may improve monetary policy pass-through in mortgage markets through easing frictions. I find that high market power FinTech lenders transmit more of monetary policy shocks to mortgage rates, while traditional banks transmit less relative to their low market power counterparts.

Second, it contributes to the mortgage literature by analyzing the funding relationships among traditional banks and FinTech lenders through the bank market power channel. Shadow banks are growing rapidly in the residential mortgage market, where they originate one quarter of all US mortgage loans. Following a tightening in monetary policy, traditional banks with market power over deposits optimally contract their deposit supply in order to earn a higher deposit spread and results in loan contraction(Drechsler, Savov, and Schnabl, 2017). On the mortgage side, Scharfstein and Sunderam (2016) looks at how market power in mortgage lending impedes the transmission of monetary policy to the housing sector.

Third, I contribute to the literature on unconventional monetary policy transmission to mortgage rates by analyzing market power in traditional banks and FinTech lenders. I study how transmission works within the same bank but with varying market power. Rodnyansky and Darmouni (2017) uses a difference-in-differences model to study the effects of large-scale asset purchases (LSAPs) on bank lending. They regress loan growth on indicator variables for LSAP interacted with a measure of each bank's exposure to mortgage-backed securities (MBS). They find that banks with higher initial holdings of MBS were more likely to increase lending. Luck and Zimmermann (2020) exploits spatial variation in bank holdings of MBS to assess the effects of LSAPs on county-level employment growth. Counties whose banks had relatively large holdings of MBS tended to experience more rapid employment growth relative to those with less exposure. Di Maggio, Kermani, and Palmer (2020) shows that the Fed's purchases of MBS are associated with a refinancing boom after quantitative easing, which in turn triggered significant equity extraction and an increase in consumption. I extend the analysis of the effect of unconventional monetary policies on the mortgage market through traditional banks and FinTech lenders.

Outline The remainder of this paper is organized as follows: Section 2 discusses the sources of data. Section 3 discusses the role of traditional banks and FinTech lenders transmitting unconventional monetary policies to mortgage rates. Section 4 investigates impulse responses against monetary policy shocks. Section 5 studies quantile regression of unconventional monetary policies to mortgage rates. Section 6 discusses empirical findings, and Section 7 concludes.

2 Data Description

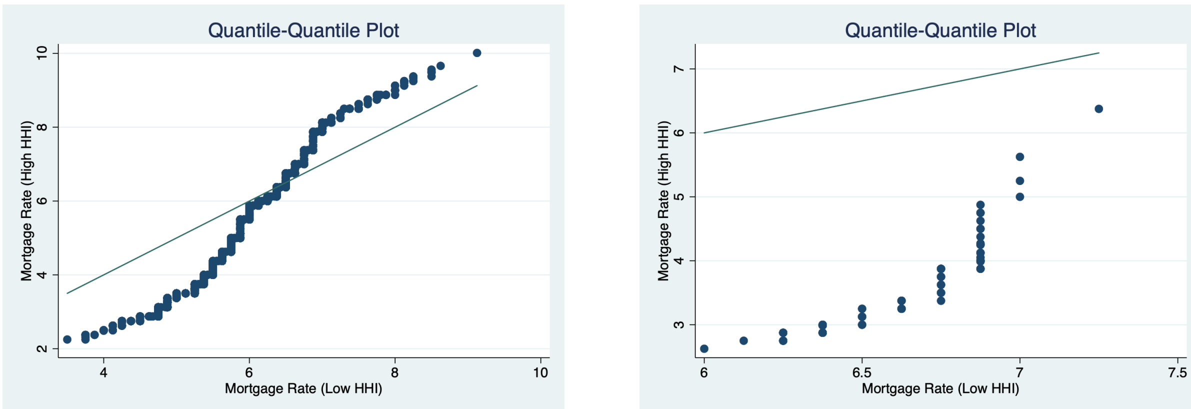
My dataset spans 2000 to 2016. I use a loan-level dataset, which includes mortgage rates, credit scores, and loan-to-value ratios from Fannie Mae's Single Family Loan Performance Data and Freddie Mac's Single Family Loan-Level Data. I obtain newly originated mortgage loans from the Home Mortgage Disclosure Act (HMDA).

I use unanticipated unconventional monetary shocks from Swanson (2021), which separately identifies unanticipated changes in the federal funds rate, forward guidance, and large-scale asset purchases for each FOMC announcement, allowing for a high-frequency identification approach. Forward guidance and LSAPs are the two main types of unconventional policies pursued by the Fed between 2009 and 2015, when the federal funds rate was essentially zero. The goal of these policies was to lower longer-term US interest rates and stimulate the economy. Forward guidance and LSAPs had substantial and highly statistically significant effects on Treasury yields, corporate bond yields, stock prices, and exchange rates, comparable in magnitude to the effects of the federal funds rate in pre-ZLB periods. In my main analysis, I focus on the forward guidance factor, which captures the FOMC communication about the likely future path of the federal funds rate over the next several quarters. It also reflects the effectiveness of announcements in pre-ZLB and ZLB periods. In the Appendix, I show that the federal funds rate factor and LSAP have a similar effect on mortgage rates as the forward guidance factor.

I measure market concentration using the HMDA, which covers 6,575 banks in 368 MSAs and 550 FinTech lenders in 151 MSAs. FinTech lenders have gained a 30% of mortgage share in 2007 to 50% of mortgage share by 2015. In my working sample, there are on average five banks and three FinTech lenders in each MSA with each bank covering 194 MSAs and each FinTech lender covering 206 MSAs. On average, there are ten banks and seven FinTech lenders and 258 MSAs per year.

Figure 1 shows that high market power banks charge lower mortgage rates in the bottom distribution of mortgage rates, whereas they charge higher mortgage rates in the top distribution of mortgage rates relative to low market power banks. High market power banks offer competitive prices at the bottom distribution of mortgage rates, but increase their markups in the higher distribution of mortgage rates. There could be a sophistication in price-setting due to market power. However, low market power FinTech lenders charge higher mortgage rates uniformly across the distribution of mortgage rates relative to high market power FinTech lenders. Traditional banks respond differently from FinTech lenders, because they have a different funding structure due to its quality of inputs. For example, traditional banks rely on deposits and equity, whereas FinTech lenders mainly depend on their net worth.

Figure 1: Quantile-Quantile Plot



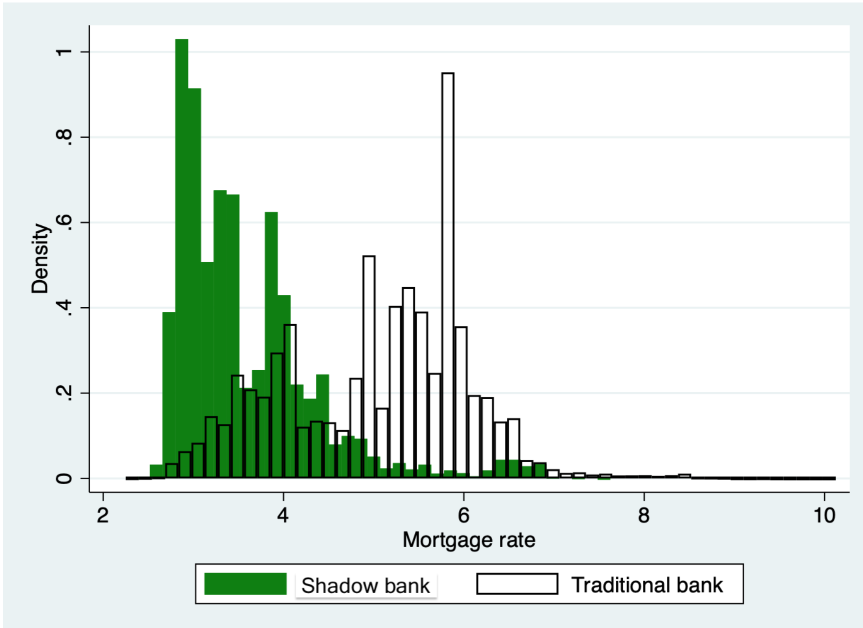
(a) All mortgage rates

(b) FinTech mortgage rates

Notes: Quantile-Quantile plot of mortgage rates by market concentration (HHI) for traditional bank and FinTech lenders.

Figure 2 shows that the mortgage rate distribution is bimodal for traditional banks, whereas it is unimodal for FinTech lenders. FinTech lenders charge lower mortgage rates than traditional banks and the rates charged by Fintech lenders span the lower distribution of traditional mortgage rates. The distribution of mortgage rates charged by traditional banks is more dispersed than the distribution of mortgage rates charged by FinTech lenders.

Figure 2: Mortgage Rate Distributions



Notes: Distribution of mortgage rates between FinTech lender and traditional bank.

3 Unconventional Monetary Policy Transmission

In this section, I discuss unconventional monetary policy transmission to the mortgage market for traditional banks and FinTech lenders. Central banks are constrained to set short-term nominal interest rate below zero, which requires the Fed to pursue unconventional monetary policies to stimulate the economy. Additionally, FinTech lenders have gained an increasingly larger share of the mortgage market after the Great Recession. However, less is known about their role in transmitting monetary policy shocks to mortgage rates. I present that high market power banks transmit monetary policy to a lesser extent relative to low market power banks. The effectiveness of monetary policy is dampened by market power in pre-ZLB periods, whereas it is amplified during ZLB periods. On the contrary, high market power FinTech lenders transmit monetary policy to a greater extent relative to low market power FinTech lenders.

In the following empirical exercises, I estimate how local market concentration affect the transmission of unconventional monetary policy shocks:

$$r_{imbt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_3 \Delta i_t \times HHI_{mt} + \Gamma HHControls_{ibmt} + \epsilon_{imbt}, \tag{1}$$

where r_{imbt} is the mortgage rate for individual i at bank b in MSA m in quarter t, α_b is bank fixed effects, and α_m is MSA fixed effects. The term Δi_t is the monetary shock from Swanson (2021). A one standard deviation increase in the forward guidance factor has no effect on the current federal funds rate, but it increases 10-year Treasury yield by 3.85 bps. The term HHI_{mt} is the local mortgage market concentration in MSA m quarter t capturing bank concentration changes over time. The term $HHControls_{ibmt}$ includes the FICO score and LTV ratio. I cluster standard errors at the bank level for correlation within banks.

My identification strategy is based on exogenous monetary policy shocks to mortgage rate changes for banks in concentrated markets. Bank fixed effects control for time-invariant differences between banks, and MSA fixed effects control for time-invariant geographical differences. For example, homeowners in New York may be savvier than households in North Dakota and, as a result, monetary policy transmits more in New York than in North Dakota. Lastly, I also include an interaction between bank and time fixed effects to control for macroeconomic conditions that affect banking decisions. I also test the interaction between bank and MSA fixed effects to see how banking decisions in different locations affect mortgage rate transmission.

Table 1 shows how traditional banks and FinTech lenders transmit monetary policy shocks onto mortgage rates. Column (1) in Panel A of Table 1 shows that, without controlling for fixed effects, in response to a 3.85 bps increase in 10-year Treasury yield, high market power banks transmit 0.69 bps less than low market power banks. Controlling for bank fixed effects in column (2) of Table 1 indicates that high market power banks transmit 0.15 bps less than low market power banks and is statistically insignificant for other specifications, indicating that location does not play a role for transmission. Columns (2), (4), and (6) in Panel A of Table 1 shows that high market power FinTech lenders transmit 2 to 3 bps more relative to low market power FinTech lenders.

High market power banks transmit monetary shocks to a lesser extent onto mortgage rates relative to low market power banks when bank fixed effects are included. On the contrary, high market power FinTech lenders allow greater pass-through onto mortgage rates relative to low market power FinTech lenders. FinTech lenders transmit more of the monetary policy shock onto mortgage rates due to its funding from investors as opposed to deposits. Deposits are cheaper sources of funding, and high market power banks leverage it by charging a constant deposit spread.

Table 1: Forward Guidance Factor

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Traditional Banks			
HHI	-1.368	-0.335	-0.0685	1.934***	-0.235	0.760
	(0.844)	(0.219)	(0.124)	(0.549)	(0.192)	(0.908)
Δi_t	0.0117	0.0586*	0	0.0776**	0	0.0340
	(0.0898)	(0.0300)	(.)	(0.0368)	(.)	(0.0256)
HHI $\times \Delta i_t$	-0.697***	-0.155**	0.0263	-0.127	0.0568	-0.104
	(0.243)	(0.0733)	(0.0338)	(0.110)	(0.0346)	(0.0775)
R^2	0.056	0.679	0.826	0.522	0.841	0.743
F	7.798	15.34	1.190	47.34	1.471	4.403
N	341200	341196	341200	341196	341127	341121
			Panel B: FinTech Lenders			
HHI	-1.679**	-0.126	-0.314	4.609***	-0.237	3.104*
	(0.533)	(0.504)	(0.227)	(1.062)	(0.246)	(1.335)
Δi_t	0.723**	0.424	0.106*	0.644	0.0810	0.616
	(0.277)	(0.239)	(0.0550)	(0.404)	(0.0635)	(0.382)
HHI$\times \Delta i_t$	1.806	2.025**	1.153	3.368*	1.097	3.225*
	(1.710)	(0.630)	(0.783)	(1.634)	(0.927)	(1.435)
R^2	0.128	0.409	0.561	0.407	0.572	0.436
F	61.92	204.2	3.406	7.354	.	3.433
N	5636	5636	5636	5597	5632	5594
Bank FE	No	Yes	No	No	No	No
Time FE	No	No	Yes	No	No	No
MSA FE	No	No	No	Yes	No	No
Bank x Time FE	No	No	No	No	Yes	No
Bank x MSA FE	No	No	No	No	No	Yes

Notes: Results from estimating

$$r_{imbt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_3 \Delta i_t \times HHI_{mt} + \Gamma HHControls_{ibmt} + \epsilon_{imbt},$$

where r_{imbt} is the mortgage rate for individual i at bank b in MSA m in quarter t, α_b is bank fixed effects, and α_m is MSA fixed effects. The term Δi_t is the monetary shock from Swanson (2021). A one standard deviation increase in the forward guidance factor has no effect on the current federal funds rate, but it increases 10-year Treasury yield by 3.85 bps. The term HHI_{mt} is the local mortgage market concentration in MSA m quarter t capturing bank concentration changes over time. The term $HHControls_{ibmt}$ includes the FICO score and LTV ratio. Standard errors are clustered at the bank level for correlation within banks. $*p < 0.1, **p < 0.05, ***p < 0.01$.

4 Local Projection Method

I use Jordà (2005)'s local projection method to understand how monetary policy shocks evolve over time and check asymmetric responses between conventional and unconventional monetary policy changes. I estimate the following regression equations at time horizons of $h = 0, ..., 4$ quarters:

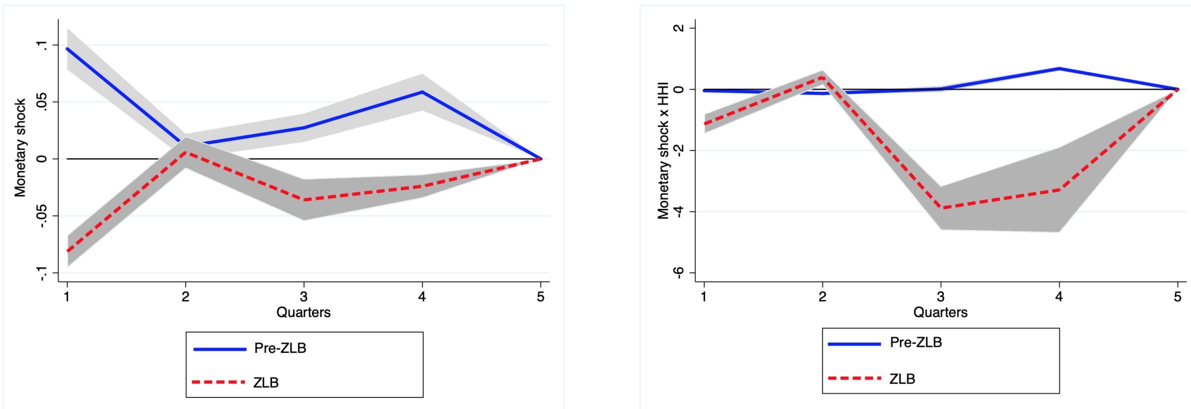
$$r^M_{b,t+h} - r^M_{b,t-1} = \alpha_{b,h} + \rho_{b,h}(L)X_{t-1} + \gamma_h \Delta i_t + \theta_h \Delta i_t HHI_{t-1} + \epsilon_{b,t+h}, \tag{2}$$

where r^M_b is the mortgage rate of bank b, $\alpha_{b,h}$ is a bank-specific fixed effect for each horizon regression, X is a set of control variables including credit score and LTV, $\rho_{b,h}(L)$ are bank-specific polynomials in lag operator L, and θ_h is an estimated response of mortgage rates at horizon h to a policy shock at time t.

Panels (a) and (b) in Figure 3 present monetary policy transmission and its interaction with market concentration to mortgage rates. Figure 3 shows an asymmetric response between pre-ZLB and ZLB periods. Panel (a) shows that banks pass-through positively pre-ZLB and negatively during ZLB periods. The solid blue line is above zero, which means that the pass-through of monetary shocks to mortgage rates is higher at higher rates. However, the dashed red line is below zero, indicating that monetary policy transmission to mortgage rates is higher at lower rates during ZLB. Panel (b) in Figure 3 shows that market concentration amplifies monetary policy transmission during ZLB, but dampens the pass-through in pre-ZLB periods. Although ZLB reduces banks' net interest margins, high market power banks need to hold long-term fixed assets in order to pay their deposit franchises.

Monetary policy transmission has been less effective pre-ZLB, but more effective during ZLB for borrowers of highly concentrated banks. A lower policy rate compresses net interest margins, as banks are unable to pass on the reduction in the policy rate to depositors. As a result, ZLB leads to a decline in bank profitability, resulting in higher monetary policy transmission to mortgage rates. However, high market power banks are incentivized to hold long-term fixed assets when policy rates are low, as they need to pay their deposit franchises. This transmits less of the monetary policy shocks to mortgage rates, because deposits are insensitive to interest rates.

Figure 3: Conventional vs Unconventional Monetary Policy



(a) Direct Effect

(b) Interacted with Market Concentration

Notes: Results from estimating $r^M_{b,t+h} - r^M_{b,t-1} = \alpha_{b,h} + \rho_{b,h}(L)X_{t-1} + \gamma_h \Delta i_t + \theta_h \Delta i_t HHI_{t-1} + \epsilon_{b,t+h}$, where r^M_b is the mortgage rate of bank b, $\alpha_{b,h}$ is a bank-specific FE, θ_h is the estimated response of mortgage rates at horizon h to the monetary policy shock at time t. Standard errors are clustered at the bank level.

5 Quantile Regression

I use quantile regression to test if highly concentrated banks transmit monetary policy differently through their distribution of mortgage rates. Quantile regression describes the relationship at different points in the conditional distribution of mortgage rates. It provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of mortgage rates, not merely its conditional mean. It is suitable for skewed data, multimodal data, or data with outliers where the behaviour at the conditional mean fails to fully capture the patterns in the data:

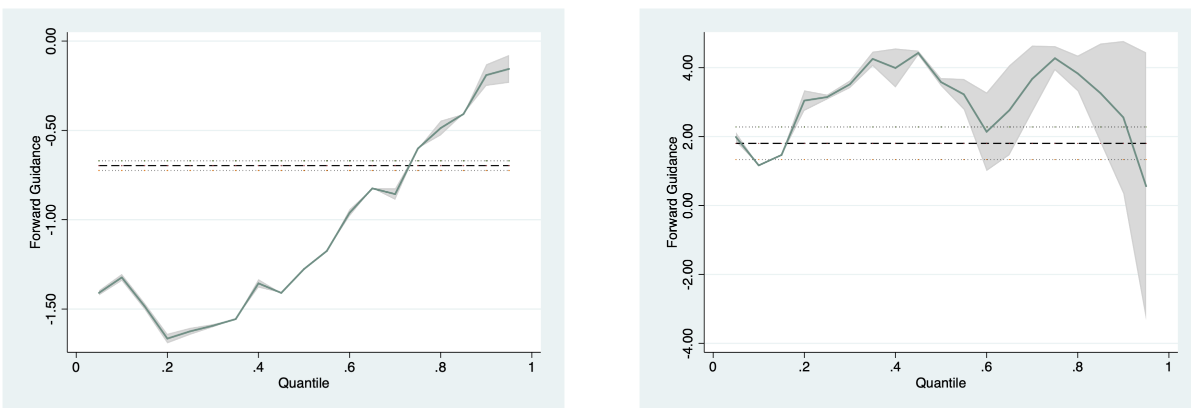
$$\begin{aligned} r_{imbt} &= \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_\theta HHI_{mt} \times \Delta i_t \\ &\quad + \Gamma HHControls_{ibmt} + u_{\theta imbt}, \end{aligned} \tag{3}$$

where r_{imbt} is the mortgage rate, Δi_t is the monetary policy shock, β_θ is the conditional quantile of r_{imbt} given Δi_t, and HHI_{mt} is market concentration. The marginal effects of market concentration given by β_θ may differ over quantiles. $HHControls$ includes credit score and LTV ratio. I cluster standard errors at the bank level for correlation within banks.

Panel (a) in Figure 4 shows that high market power banks transmit 1.5 bps less on lower quantiles of mortgage rates in contrast to 0.2 bps less on higher quantiles of mortgage rate relative to low market power banks. In order to entice borrowers, high market power banks transmit less in the bottom distribution relative to low market power banks. High market power banks also charge lower rates in the bottom distribution of mortgage rates, as borrowers are price sensitive and less willing to pay a premium, as they could easily switch to FinTech lenders.

Panel (b) in Figure 4 shows that high market power FinTech lenders pass-through 2 to 4 bps more, uniformly across its quantiles of mortgage rates. FinTech lenders rely on mortgage securitization and investors for mortgage funding and transmit more monetary policy due to their expensive sources of funding. Although FinTech lenders do not face any regulatory costs, they face higher funding sources resulting in net higher transmission.

Figure 4: Quantile Regression: Mortgage Rates



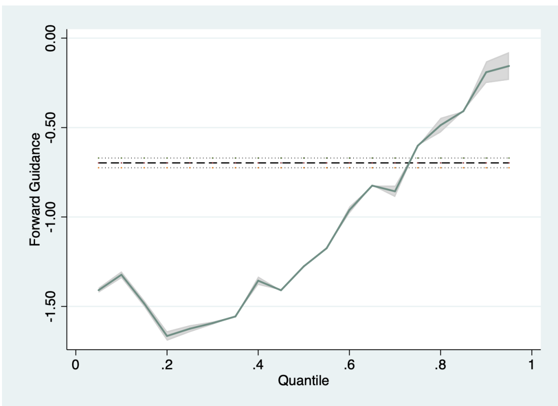
(a) Traditional Banks

(b) FinTech Lenders

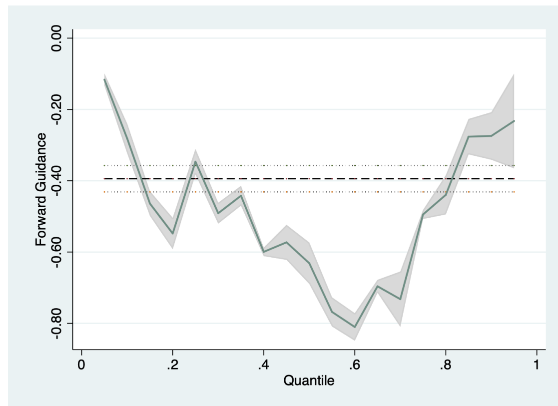
Notes: Results from estimating $r_{imbt} = \alpha_b + \alpha_m + \alpha_t + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_\theta HHI_{mt} \times \Delta i_t + \Gamma HHControls_{ibmt} + u_{\theta imbt}$, where r_{imbt} is the mortgage rate, Δi_t is the monetary policy shock, β_θ is the conditional quantile of r_{imbt} given Δi_t, and $HHControls_{ibmt}$ includes borrower's credit score and LTV. Standard errors are clustered at the bank level.

Then, I analyze how highly concentrated banks respond to conventional and unconventional monetary shocks at different quantiles of mortgage rates. First, panel (a) in Figure 5 shows that high market power banks transmit less to mortgage rates at the bottom of the distribution than at the top. High market power banks have sophistication in mortgage rate-setting. Second, highly concentrated banks respond less to monetary shocks relative to banks in competitive markets. Highly concentrated banks transmit less in order to entice borrowers in the lower distribution of mortgage rates, as these borrowers are price sensitive. Third, panel (b) shows that the magnitude of transmission to mortgage rates at the lower end of the distribution has increased from pre-ZLB to ZLB periods. High market power banks transmit the least in the lower distribution pre-ZLB, but they increase transmission in the bottom distribution during ZLB periods. Due to the net interest margin, high market power banks are transmitting less in the bottom distribution of mortgage rates during the ZLB period.

Figure 5: Quantile Regression: Conventional vs Unconventional Monetary Policy



(a) Pre-ZLB



(b) ZLB

Notes: Results from estimating $r_{imbt} = \alpha_b + \alpha_m + \alpha_t + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_\theta HHI_{mt} \times \Delta i_t + \Gamma HHControls_{ibmt} + u_{\theta imbt}$, where r_{imbt} is the mortgage rate, Δi_t is the monetary policy shock, $\Delta i_t' \beta_\theta$ is the conditional quantile of r_{imbt} given Δi_t, and $HHControls_{ibmt}$ include borrower's credit score and LTV. Standard errors are clustered at the bank level. Pre-ZLB is monetary policy before 2009 and ZLB is monetary policy between 2009 and 2016.

6 Discussion

Mortgage rates are bimodal for traditional banks and highly dispersed relative to FinTech lenders. FinTech lenders charge lower mortgage rates than traditional banks. High market power banks charge lower mortgage rates in the bottom distribution and higher mortgage rates in the top distribution relative to low market power banks. High market power FinTech lenders charge lower mortgage rates than low market power FinTech lenders throughout the mortgage rate distribution.

High market power banks transmit monetary policy shocks less than low market power banks. In particular, they transmit the least in the bottom distribution relative to low market power banks. High market power FinTech lenders pass-through more relative to low market power FinTech lenders. Traditional banks and FinTech lenders have different sources of funding and regulatory costs resulting in different transmissions to mortgage rates.

Monetary policy transmission is higher at higher policy rates pre-ZLB, and it is higher at lower policy rates during ZLB. However, highly concentrated banks dampen the effectiveness of monetary policy pre-ZLB, whereas they amplify it during ZLB. High market power banks have a deposit franchise, where they borrow deposits at rates that are both low and insensitive to the policy rate. Running a deposit franchise incurs high operating costs through branches and advertising, but these costs do not vary much over time and are hence insensitive to the policy rate. As a result, high market power banks have incentives to hold long-term fixed assets when policy rates are lower in order to pay high operating costs.

7 Concluding Remarks

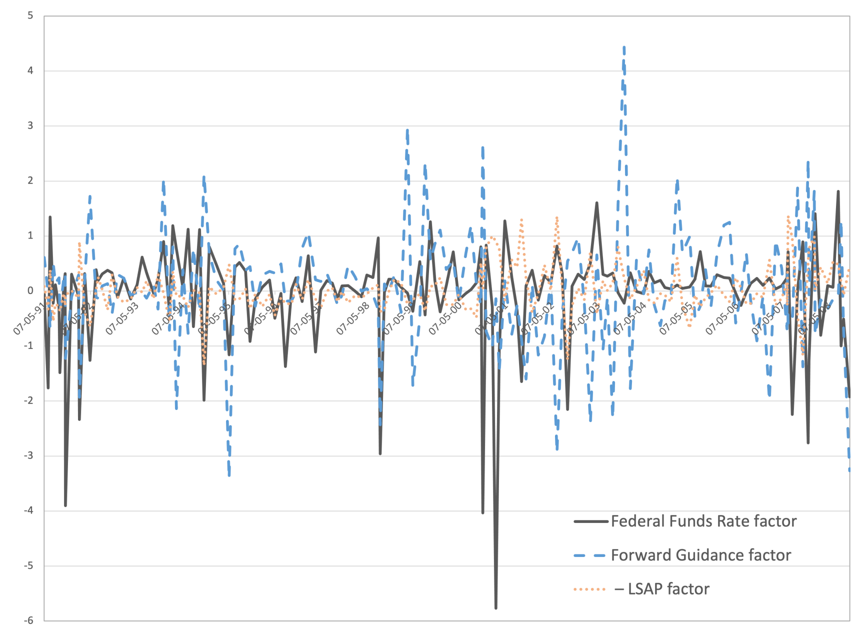
This paper analyzes how traditional banks and FinTech lenders transmit unconventional monetary policy to mortgage rates via the bank market power channel. I show that, in response to a 3.85 bps increase in 10-year Treasury yield, high market power banks transmit 0.15 to 0.69 bps less to mortgage rates relative to low market power banks. In contrast, high market power FinTech lenders pass-through 2 to 3.36 bps more relative to low market power FinTech lenders. Although FinTech lenders do not face any regulatory costs, their expensive sources of funding from investors results in higher transmission of monetary policy shocks to mortgage rates, while traditional banks leverage deposit franchises and transmit less.

Lastly, monetary policy transmission is higher at higher policy rates in periods before zero lower bound (pre-ZLB) and it is higher at lower policy rates during ZLB. The effectiveness of monetary policy is dampened by market power pre-ZLB, but it is amplified by high market power banks during ZLB. Although the ZLB reduces banks' net interest margins, high market power banks need to hold mortgage rates when policy rates are lower in order to pay their deposit franchises.

8 Appendix

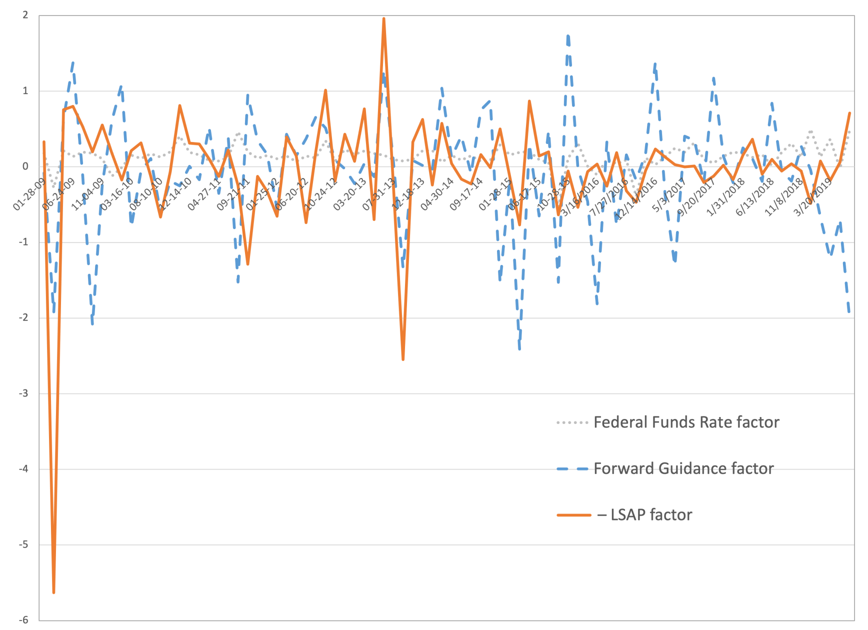
8.1 Figures

Figure 6: Pre-ZLB Monetary Policy Shocks



Notes: Federal funds rate, forward guidance, and LSAP factors from Swanson (2021) is shown before 2009 (pre-ZLB).

Figure 7: ZLB Monetary Policy Shocks



Notes: Federal funds rate, forward guidance, and LSAP factors from Swanson (2021) is shown after 2009 (ZLB).

8.2 Tables

Table 2: Summary Statistics: Market Concentration

Variables	Mean	Std. Dev.	Min	P25	P50	P75	Max
Fannie Mae and Freddie Mac							
Lerner index	0.72	0.26	0.14	0.57	0.79	0.96	0.99
Banks in each MSA	77.69	12.92	1	69	79	88	99
MSA per year quarter	427.69	9.19	413	425	427	434	443
Banks per year quarter	24.15	3.12	18	22	24	27	31
MSAs per each bank	361.27	83.89	11	330	391	426	443
Home Mortgage Disclosure Act							
Market concentration ($000)	0.19	0.18	0	0.07	0.13	0.25	1
Market concentration (#)	0.19	0.18	0	0.07	0.13	0.24	1
Banks in each MSA	267.2	264.5	1	84	175	359	1072
MSA per year quarter	368.7	32.3	305	317	383	392	396
Banks per year quarter	6574.5	961.9	3427	6270	6654	7323	7605
MSAs per each bank	47.3	93.4	0	1	2	23	352
Mortgage Loan (#)	188.79	1605.72	0	5	26	93	224902
Mortgage Loan ($000)	29451.36	297829.8	0	667	3482.5	13170	37,100,000
Merged Sample							
Market concentration ($000)	0.19	0.17	0.03	0.04	0.14	0.25	1
Market concentration (#)	0.17	0.16	0.02	0.04	0.14	0.24	1
Lerner index	0.84	0.14	0.05	0.78	0.82	0.96	0.98
Banks in each MSA	5.68	7.39	1	3	4	5	36
MSA per year quarter	258.98	152.47	3	51	352	356	365
Banks per year quarter	16.59	3.36	5	15	17	19	25
MSAs per each bank	194.09	107.83	1	112	163	335	335

Notes: *Lerner index* is measured as $LI = \frac{r_t^M - ffr_t}{ffr_t}$ from Fannie Mae and Freddie Mac. LI is highly concentrated due to large banks in the sample, thus it is not used in the regression analysis. In Fannie Mae and Freddie Mac dataset, there are 77 banks in each MSA and 24 banks per quarter. There are 427 MSAs per quarter and 361 MSAs per each bank. Market concentration is competitive in HMDA dataset. There are 267 banks in each MSA and 47 MSAs per each banks. There are 6574 banks per quarter and 368 MSA per quarter. Banks on average make 29M$ loans and issue 188 thousand of loans per quarter.

Table 3: Correlation between Monetary Policy Shocks

	FFR	FG	LSAP	Policy news shock
FG	-0.2528			
LSAP	0.0734	0.0605		
Policy news	0.5616	0.5560	0.3074	
FFR shock	0.7177	-0.0281	0.0507	0.6738

Notes: Federal funds rate factor (FFR), forward guidance factor (FG), LSAP factor are from Swanson (2021). Policy news shock and FFR shock are from Nakamura and Steinsson (2018).

Table 4: Federal Funds Rate Factor

	(1)	(2)	(3)	(4)	(5)	(6)
				Panel A: Traditional Banks		
HHI	-0.893	-0.287	-0.0291	2.039***	-0.119	0.799
	(1.001)	(0.220)	(0.101)	(0.576)	(0.185)	(0.924)
FFR Factor	0.597**	0.0807***	0	0.202**	0	0.0546
	(0.254)	(0.0228)	(.)	(0.0797)	(.)	(0.0381)
HHI ×FFR Factor	-0.994*	-0.232**	-0.127	-0.204	-0.250***	-0.149*
	(0.544)	(0.0909)	(0.0792)	(0.175)	(0.0700)	(0.0802)
R^2	0.098	0.677	0.826	0.525	0.841	0.743
F	8.668	6.606	2.350	6.598	36.54	4.263
N	341200	341196	341200	341196	341127	341121
				Panel B: FinTech Lenders		
HHI	-1.744	0.318	0.0416	1.996	0.0600	0.368
	(1.506)	(0.507)	(0.246)	(1.445)	(0.290)	(0.736)
FFR Factor	1.644*	0.576	0.642	0.452	0.679	0.642
	(0.861)	(0.669)	(0.692)	(0.678)	(0.698)	(0.659)
HHI×FFR Factor	0.668	-1.125	-0.235	-1.546	-0.0593	-0.773
	(3.028)	(2.397)	(1.496)	(2.543)	(1.392)	(2.381)
R^2	0.146	0.423	0.577	0.405	0.588	0.438
F	1865.2	13.82	0.586	1.730	.	8.284
N	5636	5636	5636	5597	5632	5594
Bank FE	No	Yes	No	No	No	No
Time FE	No	No	Yes	No	No	No
MSA FE	No	No	No	Yes	No	No
Bank x Time FE	No	No	No	No	Yes	No
Bank x MSA FE	No	No	No	No	No	Yes

Notes: Results from estimating $r_{imbt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_3 \Delta i_t \times HHI_{mt} + \Gamma \text{HH Controls}_{ibmt} + \epsilon_{imbt}$ where α_b is bank fixed effect, α_m is MSA fixed effect, HHI_{mt} is the HHI in the mortgage market, Δi_t is a monetary policy shock from Swanson (2021), HH Controls_{ibmt} include borrower's credit score and LTV. Standard errors are clustered at the bank level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table 5: LSAP

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Traditional Banks					
HHI	-1.412*	-0.416**	-0.0812	1.822***	-0.259	0.749
	(0.797)	(0.204)	(0.128)	(0.523)	(0.182)	(0.905)
LSAP Factor	0.800***	0.182***	0	0.408***	0	0.184***
	(0.136)	(0.0419)	(.)	(0.0562)	(.)	(0.0440)
HHI ×LSAP Factor	-1.131**	-0.340**	-0.125*	-0.771***	-0.219*	-0.390**
	(0.474)	(0.133)	(0.0690)	(0.157)	(0.122)	(0.151)
R^2	0.140	0.680	0.826	0.537	0.841	0.746
F	33.92	8.717	1.887	20.98	1.629	6.869
N	341200	341196	341200	341196	341127	341121
	Panel B: FinTech Lenders					
HHI	-1.722	0.202	0.0840	1.793	0.146**	0.390
	(1.468)	(0.141)	(0.0463)	(1.376)	(0.0482)	(0.641)
LSAP Factor	0.181	0.126	0.181	0.0958	0.166	0.109
	(0.172)	(0.151)	(0.128)	(0.148)	(0.153)	(0.134)
HHI×LSAP Factor	0.845	0.775**	0.619**	0.945**	0.689**	0.852**
	(0.478)	(0.290)	(0.254)	(0.372)	(0.286)	(0.343)
R^2	0.177	0.484	0.658	0.468	0.668	0.496
F	1008.8	4.494	6.683	3.760	.	2.710
N	5636	5636	5636	5597	5632	5594
Bank FE	No	Yes	No	No	No	No
Time FE	No	No	Yes	No	No	No
MSA FE	No	No	No	Yes	No	No
Bank x Time FE	No	No	No	No	Yes	No
Bank x MSA FE	No	No	No	No	No	Yes

Notes: Results from estimating $r_{imbt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 HHI_{mt} + \beta_3 \Delta i_t \times HHI_{mt} + \Gamma \text{HH Controls}_{ibmt} + \epsilon_{imbt}$ where α_b is bank fixed effect, α_m is MSA fixed effect, HHI_{mt} is the HHI in the mortgage market, Δi_t is a monetary policy shock from Swanson (2021), HH Controls$_{ibmt}$ include borrower's credit score and LTV. Standard errors are clustered at the bank level. $***p < 0.01, **p < 0.05, *p < 0.1$.

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