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Monetary Policy Transmission Through Shadow and Traditional Banks

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Abstract

I investigate how monetary policy transmits to mortgage rates via the mortgage market concentration channel for both traditional and shadow banks in the United States from 2009 to 2019. On average, shadow and traditional banks exhibit only a slight disparity in transmitting monetary shocks to mortgage rates. Nonetheless, in highly concentrated mortgage markets, shadow banks transmit marginally 35 basis points (bps) more, whereas traditional banks transmit marginally 25 bps less in response to a monetary policy surprise of more than 100 bps. Lastly, banks serve different parts of the mortgage rate distribution: (i) fintech lenders compete with traditional banks for the highest rates, (ii) traditional banks target primarily the middle of the mortgage rate distribution, and (iii) non-fintech lenders specialize in the lowest rates by transmitting monetary policy the least.

Topics: Financial institutions; Interest rates; Monetary policy transmission
JEL codes: E44, E52, G21

Résumé

J’étudie la transmission de la politique monétaire aux taux hypothécaires par le canal de la concentration du marché hypothécaire, tant pour les banques traditionnelles que pour les banques parallèles aux États-Unis, de 2009 à 2019. En moyenne, la transmission des chocs de politique monétaire aux taux hypothécaires est pratiquement équivalente pour ces deux catégories de banques. Par contre, si on compare avec les marchés hypothécaires très concentrés, on constate qu’un relèvement inattendu de 100 points de base du taux directeur entraîne une transmission de 35 points de plus pour les banques parallèles et de 25 points de moins pour les banques traditionnelles. Enfin, ces institutions financières ciblent différents segments de la distribution des taux hypothécaires : 1) les banques parallèles du secteur des technologies financières font concurrence aux banques traditionnelles pour les prêts aux taux les plus élevés; 2) les banques traditionnelles visent surtout le milieu de la distribution des taux; 3) les banques parallèles hors du secteur des technologies financières se spécialisent dans les prêts aux taux les plus bas et sont les plus petits vecteurs de la politique monétaire.

Sujets : Institutions financières; Taux d'intérêt; Transmission de la politique monétaire
Codes JEL : E44, E52, G21

1 Introduction

Shadow banks are gaining a larger share of the mortgage lending market, and they have the potential to reshape the transmission of monetary policy. In 2013, the top three lenders were traditional banks, but by 2019, Quicken Loans and United Shore Financial had taken the top spot, replacing JPMorgan Chase and Bank of America (Corbae et al., 2023). Online mortgage accessibility has reduced search costs, expanded geographic reach, and intensified competition in financial markets. While previous research has primarily focused on how traditional banks transmit monetary shocks to mortgage rates, the impact on shadow banks and differences between FinTech and non-FinTech lenders remain less explored.

In this paper, I study how monetary policy affects mortgage rates through the mortgage market concentration channel, focusing on both traditional and shadow banks. Shadow banks are non-depository lenders with a strong online presence that do not face regulatory constraints. Shadow banks can either rely on automated loan processing with a focus on refinancing (FinTech) or rely on online banking with loan officers involved in earlier stages (non-FinTech). Thus, following Buchak et al. (2018b), I classify institutions originating mortgage loans into three types: traditional banks, FinTech lenders, and non-FinTech lenders.

I empirically explore the heterogeneous transmission of monetary policy across lender types, market concentration intensity, and mortgage rates. I combine three loan-level datasets: Fannie Mae's Single-Family Loan Performance Data, Freddie Mac's Single-Family Loan-Level Dataset, and the Home Mortgage Disclosure Act (HMDA) from 2009 to 2019. I use the HMDA to construct a market concentration index because it contains information on mortgage originations by 90% of US lenders. I exploit the borrower characteristics and geographical variation of mortgage rates from the Fannie Mae and Freddie Mac datasets.

First, I find that, on average, in highly concentrated markets, shadow banks amplify the impact of monetary policy while traditional banks dampen the positive monetary policy surprise to mortgage rates. If instead I do not account for differences in market concentration, traditional and shadow banks would not exhibit economically significant differences in their transmission of monetary policy to mortgage rates. In highly concentrated markets, FinTech and non-FinTech lenders pass through 35 basis points (bps) marginally more while traditional banks transmit 25 bps marginally less in response to a +100 bps increase in monetary surprises. Traditional banks exercise their market power by borrowing deposits at rates that are both low and unaffected by changes in the policy rate (Drechsler et al., 2021). Traditional banks transmit monetary policy less to mortgage rates because they invest in long-term assets to fund themselves with short-term deposits. On the contrary, shadow banks rely on investors for funding, making them more responsive to monetary policy changes due to costlier changes in funding. In addition, shadow banks are more responsive because they can adjust their mortgage supplies more flexibly because of their investments in information technology (Modi et al., 2022; Fuster et al., 2019; Berg et al., 2022; Buchak et al., 2018b).

Second, I find that traditional and shadow banks cater to different segments of the distribution of mortgage rates. For that purpose, I use quantile regressions to analyze how banks in highly concentrated markets transmit monetary policy across the distribution of mortgage rates. I am the first to document U-shaped and M-shaped relationships in how monetary policy affects mortgage rates for traditional banks and FinTech lenders in highly concentrated markets, respectively. At the *bottom of the distribution* of mortgage rates, shadow banks transmit monetary shocks marginally the least, while traditional banks transmit marginally the most. Despite relying on costly investor funding as a source of financing, shadow banks leverage their technological advancements to strategically absorb the increased funding costs and thereby achieve a relatively lower monetary policy transmission to the bottom 10% of the mortgage rate distribution. In the *middle of the distribution* of mortgage rates, i.e., for mortgage rates that are not too low nor too high, traditional banks transmit marginally the least, while shadow banks transmit the most within this range. Traditional banks in highly concentrated markets absorb additional funding costs to keep their market share in this range. At the *top of the distribution* of mortgage rates, both FinTech lenders and traditional banks compete for the top 10% of the mortgage rates by transmitting monetary shocks marginally the least.

To explain the results obtained from quantile regression, I develop a simple model of third-degree price discrimination in which consumers differ along dimensions of willingness-to-pay and willingness-to-switch. I build on early theoretical work on oligopoly price discrimination, which shows that competition can increase or decrease price differences. Fannie Mae and Freddie Mac show that traditional banks attract first-time home buyers more than other lenders, suggesting price sensitivity among their customers. FinTech lenders, on the other hand, cater to borrowers with lower debt-to-income ratios, indicating higher income and a greater willingness to pay. This suggests that these borrowers may prioritize convenience, leading them to choose FinTech lenders (Fuster et al., 2019). Non-FinTech lenders, however, serve borrowers with high unpaid principal balances. Those with larger loans are more inclined to seek lower mortgage rates and are more willing to switch lenders (Buchak et al., 2018b). Under theoretical considerations, I find that non-FinTechs can transmit very high to mortgage rates under monopoly but not when there is competition. On the contrary, traditional banks cannot transmit very high to mortgage rates even under a monopoly, so competition does not impact their rates much. Lastly, FinTechs can transmit high to mortgage rates even under competition, and competition also does not impact their mortgage rates.

Related Literature This paper contributes to three strands of the literature. First, I contribute to the existing literature on monetary policy transmission in the mortgage market by investigating the impact of competition between traditional and shadow banks on pass-through. Using novel shadow bank funding data, Jiang, Matvos, Piskorski, and Seru (2020) find that shadow bank debt is funded by their competitors. Jiang (2019) find that traditional banks have market power in the upstream market for shadow banks' funding, leading to less competition in the downstream mortgage origination market. Buchak, Matvos, Piskorski, and Seru (2018a) discover that FinTech lenders with shorter time-to-sale have a competitive advantage in mortgage lending and impact competition in the mortgage market. Fuster, Plosser, Schnabl, and Vickery (2019) study how technology affects mortgage lending and discover that it can improve monetary policy pass-through by reducing frictions such as slow processing times and suboptimal refinancing. I find that in highly concentrated markets, shadow banks transmit monetary policy shocks to mortgage rates marginally more, while traditional banks transmit marginally less.

Second, I contribute to the mortgage literature by analyzing the funding relationships between traditional and shadow banks, with a particular focus on the role of mortgage market concentration. The increasing presence of shadow banks in the residential mortgage market, accounting for a quarter of all US mortgage loans, has made this a critical area of investigation. Specifically, I investigate how traditional banks with market power over deposits respond to monetary policy tightening by reducing their deposit supply, thereby increasing their deposit spread and resulting in a contraction of lending (Drechsler, Savov, and Schnabl, 2017). Xiao (2020) shows that shadow bank deposits expand during periods of monetary tightening due to the large fraction of household savers while commercial bank deposits contract because yield-oriented investors search for alternative options. On the mortgage side, Scharfstein and Sunderam (2016) look at how market power in mortgage lending impedes the transmission of monetary policy to the housing sector. I extend the analysis by investigating how shadow and traditional banks differ in their transmission of monetary shocks to mortgage rates.

Third, I contribute to the literature on oligopoly price discrimination. A growing body of research analyzes the impact of market structure on equilibrium outcomes in the context of price discrimination (Stole, 2007). Several studies explore how competition influences price dispersion in scenarios where firms engage in third-degree price discrimination. Price discrimination occurs when firms charge varying mark-ups to different customers. While common intuition might suggest that competition would restrict a firm's ability to engage in price discrimination, it is firmly established that such practices can persist in non-monopoly environments. Initial models of price discrimination were formulated within a monopoly framework, focusing solely on differences in consumers' underlying willingness-to-pay. However, in the context of oligopoly price discrimination, consumers' willingness-to-switch becomes a relevant factor (Borenstein, 1985; Holmes, 1989; Stole, 2007). The association between competition and increased price dispersion was initially documented by Borenstein and Rose (1994). Chandra and Lederman (2018) revisit the relationship between competition and price discrimination and show empirically the sources of consumer heterogeneity for price differences. However, Gerardi and Shapiro (2009) observe the opposite pattern. Given this ambiguity, I reexamine the correlation between market structure and mortgage rate dispersion across different types of lenders.

Outline The remainder of this paper is organized as follows: Section 2 describes the sources of data. Section 3 constructs the residualized mortgage rates and describes the identification strategy. Section 4 analyzes the role of traditional and shadow banks in transmitting monetary policies to mortgage rates. Section 5 studies how monetary policies transmit to mortgage rate distributions using quantile regression. Section 6 lays out the theoretical considerations to explain quantile regression results. Section 7 concludes.

2 Data description

I combine three different datasets: (1) Fannie Mae's Single-Family Loan Performance Data and Freddie Mac's Single-Family Loan-Level Data for loan-level mortgage rates, (2) Home Mortgage Disclosure Act (HMDA) data for mortgage originations to construct a market concentration index, and (3) monetary policy shocks identified by Bauer and Swanson (2023). The analysis is conducted for the period between 2009Q1 and 2019Q2, and the unit of observation is at the quarter-MSA-bank level.

2.1 Monetary shocks

The data on high-frequency financial market reactions to Federal Open Market Committee (FOMC) announcements come from the widely used dataset of Bauer and Swanson (2023). This dataset contains the changes in financial variables in a 30-minute window around FOMC announcements (from 10 minutes before to 20 minutes after the announcement). Monetary policy surprises focus on interest rate changes in a narrow window of time around FOMC announcements to rule out reverse causality and other endogeneity problems. FOMC decisions are completed an hour or two before the decision is announced, implying that the FOMC could not have been reacting to changes in financial markets in a sufficiently narrow window of time around the announcement. I focus on monetary shocks from 2009Q1 to 2019Q2.

2.2 Fannie Mae and Freddie Mac

Loan-level mortgage rates are obtained from Fannie Mae's Single-Family Loan Performance Data and Freddie Mac's Single-Family Loan-Level Dataset. Both datasets include a subset of the 30-year, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages acquired by government-sponsored enterprises (GSEs). The data include both borrower and loan information at the time of origination as well as data on the loan's performance. The data consists of the borrower's credit (FICO) score, the date of origination, the loan size, the loan size relative to the house value (LTV ratio), whether the loan is originated for purchase or refinancing, the MSA code of the property, and the interest rate on the mortgage.

I pool data from both the Fannie Mae and Freddie Mac datasets because the combination covers the majority of conforming loans issued in the US. I use loans associated with both new-purchase mortgages and refinancings. My sample includes roughly 26 million loans that originated during the 2009 to 2019 period. It covers the largest 35 lenders. I aggregate mortgage rates and borrower characteristics at the quarter-MSA-bank level.

Table 1: Summary statistics

	Traditional		FinTech		Non-FinTech	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Unpaid principal balance	228075.6	121511.1	185996	102226.8	236741.5	138950.8
DTI	33.2	9.95	32.06	9.76	34.6	9.81
Credit score	751.94	47.13	748.9	51.95	748.23	48.1
LTV	72.24	20.17	77.29	25.3	75.82	24.06
Mortgage rates	4.3	.63	3.91	.59	4.3	.61
HHI	.25	.24	.63	.31	.25	.21
Log(mortgage amount)	3.02	1.83	7.17	2.44	3.98	1.49
Log(mortgage volume)	9.5	3.56	11.67	2.15	12.19	4.12

Notes: Summary statistics are based on the Fannie Mae and Freddie Mac datasets from 2009Q1 to 2019Q2 for US lenders. Traditional banks are depository institutions, are subject to tighter regulations, and hold a significant fraction of their loan originations on the balance sheet. Shadow banks are defined as non-depository lenders who fund their originations through securitization financed with short-term securities. Shadow banks consist of FinTech and non-FinTech lenders. FinTech lenders are shadow banks that have a strong online presence where nearly all of the mortgage application process takes place online, while non-FinTech lenders issue mortgages online with loan officers in the earlier stages of the mortgage process.

Table 1 shows that traditional banks and FinTech lenders compete for similar types of consumers. However, there is a subtle difference in borrower characteristics between non-FinTech lenders and the other two lenders. For example, traditional banks and FinTech lenders tend to issue mortgages to households with higher credit scores than non-FinTech lenders. On the other hand, non-FinTech lenders serve customers with higher LTV ratios than traditional banks and FinTech lenders. In addition, each lender has their own distinct market segment. For instance, traditional banks have a higher fraction of first-time home buyers, indicating that their customers are price sensitive. Next, FinTech lenders have borrowers with lower DTI, indicating that they have higher incomes and as a result have high willingness-to-pay. This potentially suggests that these borrowers value convenience and as a result borrow from FinTech lenders (Buchak et al., 2018b). Lastly, non-FinTech lenders have borrowers with high unpaid principal balances. Borrowers with high loan size are more likely to search for lower mortgage rates and have high willingness-to-switch across lenders.

2.3 Home Mortgage Disclosure Act (HMDA)

Mortgage origination comes from the HMDA dataset, which covers about 90% of the mortgage applications and approvals in the US. The dataset provides the loan amount, loan type and purpose, property location, and some borrower characteristics, such as gender, race, and income.

The dataset contains the originator's identity, which allows for linking with the mortgage rate information present in the Fannie Mae and Freddie Mac datasets. The HMDA dataset discloses information about home mortgages from the majority of US financial institutions, including shadow banks, which enables me to identify traditional banks, FinTech lenders, and non-FinTech lenders. I complement the dataset with lender identifications from Buchak et al. (2018b). I focus on the period from 2009 to 2019 because shadow banks started to grow after the Great Financial Crisis. The HMDA dataset also records whether the loan is retained on the originator's balance sheet or sold within the origination year to a third party such as GSEs or private-label securitization identities. I restrict the sample to home mortgages for 30-year fixed mortgages for single-family homes, which corresponds to the majority of the applications.

I use the data from HMDA to compute the Herfindahl-Hirschman Index (HHI) to measure market concentration using mortgage shares in the local market (MSA) for each bank. The traditional way of constructing market concentration is by summing mortgage market shares squared:

$$\text{HHI}_{mt} = \sum_{b \in \{m\}} \Big(\frac{mtg_{bmt}}{\sum_{b \in \{m\}} mtg_{bmt}} \Big)^2$$

where mtg_{bmt} is the mortgages of bank b in MSA m in year t, $\sum_{b \in \{m\}} mtg_{bmt}$ is the total mortgages in MSA m in year t, and HHI_{mt} is the sum of mortgage market shares squared. The HMDA covers 6,575 banks in 368 MSAs and 550 FinTech lenders in 151 MSAs. FinTech lenders have increased their mortgage share from 30% in 2007 to 50% in 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 10 banks, 7 FinTech lenders, and 258 MSAs per year.

3 Empirical approach

In this section, I describe how I construct residualized mortgage rates after purging out borrower and loan characteristics. Then I discuss my identification strategy for potential endogeneity problems.

3.1 Residualized mortgage rates

I take out borrower characteristics such as credit score and LTV ratios, bank fixed effects, and MSA fixed effects from mortgage rates by running a regression:

$$r_{imbt} = \alpha_m + \alpha_b + \alpha_1 X_{it} + \eta_{imbt},$$

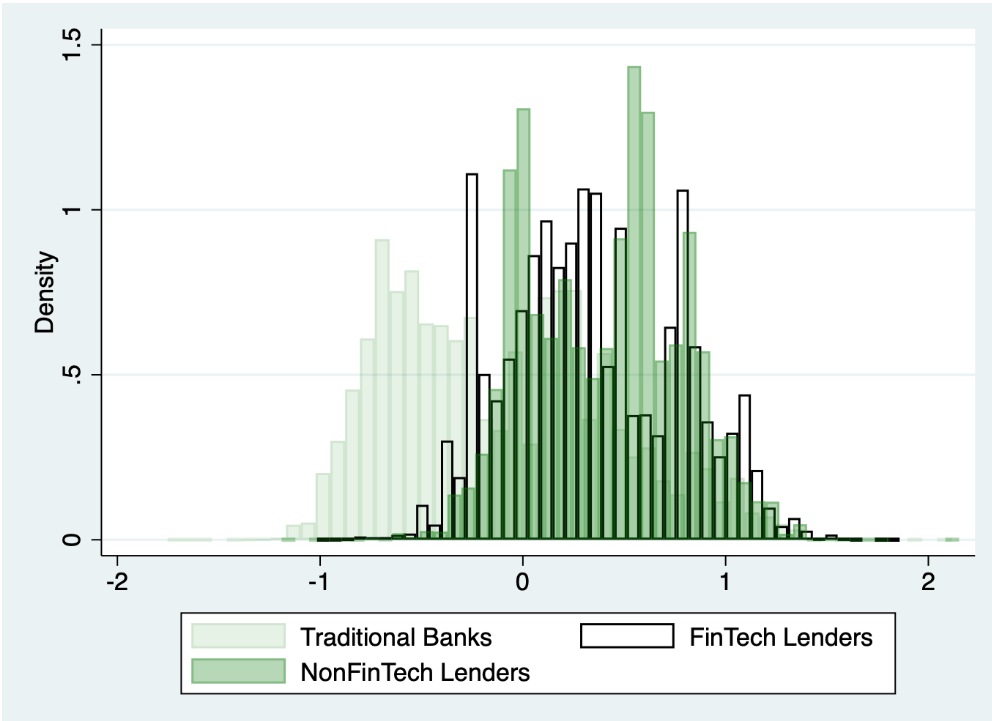
where r_{imbt} is the mortgage rate for individual i, MSA m, and bank b at period t. X_{it} captures borrower characteristics such as credit score and LTV, and η_{ibmt} is the residual mortgage rate. Then I compute lender-specific average mortgage rates from the residuals:

$$R_{mbt} = \frac{1}{N_{mbt}} \sum_{i=1}^{N_{mbt}} \eta_{imbt}$$

where N_{mbt} is the number of loans by bank b in the MSA m during period t. Formally, R_{mbt} is the average mortgage rate residual in an MSA for loans originated during a given period for a given sample.

I document that banks have heterogeneous residuals that could not be explained by borrower characteristics, banks, or geographic locations. However, this residual still contains interactions between bank and year, borrower characteristics and year, and MSA and year fixed effects. Banking, borrower, and MSA characteristics that vary over the business cycle are left in the residual. Figure 1 shows that the distribution of mortgage rates at traditional banks is more dispersed. There is an overlap of all lenders in the middle of the mortgage rate distribution.

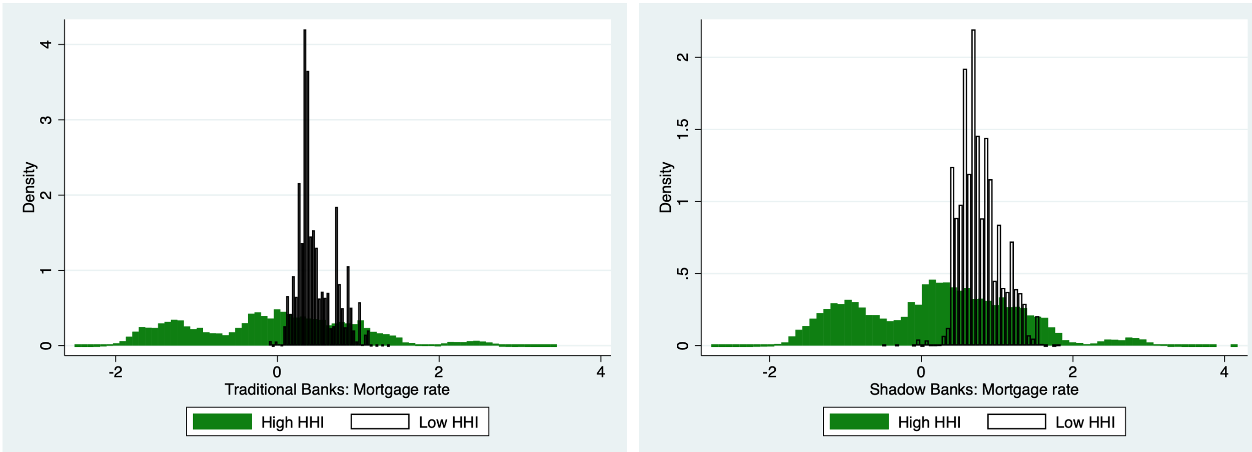
Figure 1: Unexplained mortgage rate residuals



Notes: This figure depicts heterogeneous mortgage rate residuals across lenders after controlling for borrower characteristics, MSA, and bank fixed effects.

Figure 2 shows that banks in highly concentrated markets offer a wider range of mortgage rates than banks in competitive markets. A larger span of mortgage rates indicates that banks in highly concentrated markets have the ability to exert their market power in setting mortgage rates. A wider dispersion of mortgage rates in highly concentrated markets is evident in both traditional and shadow banks. Higher concentration in the shadow banking sector indicates large entry barriers, technological quality differences, and implicit guarantees that government agencies offer to shadow banks.

Figure 2: Herfindahl-Hirschman Index (HHI)



(a) Traditional banks

(b) Shadow banks

Notes: This figure shows that banks operating in highly concentrated markets have a wider range of mortgage rates, while banks in competitive markets have mortgage rates distributed in a narrow range.

3.2 Identification

In the empirical models used in the next two sections, my identification strategy relies on several key components to analyze the transmission of monetary policy to the mortgage rates, particularly focusing on the competition between traditional and shadow banks. I use bank fixed effects to control for supply and time-invariant differences between banks. Additionally, I introduce an interaction term between bank and year fixed effects to account for macroeconomic conditions that impact banking decisions.

I incorporate an interaction between MSA and year fixed effects into the analysis to address demand-side factors. This facet of the identification strategy is essential in capturing the potential influence of the expanding online presence of shadow banks in the mortgage market on the competition with traditional banks. I use MSA interactions with year fixed effects to explore how the changing landscape of online competition may impact the dynamics of mortgage rates, especially concerning the growing role of shadow banks.

I incorporate MSA fixed effects to control for time-invariant geographical differences. For example, homeowners in New York may be savvier than households in North Dakota, potentially affecting how monetary policy transmits in these areas. To further explore this aspect, I use the interaction between bank and MSA fixed effects, shedding light on how banking decisions in different geographical locations influence the transmission of monetary shocks to mortgage rate changes.

I use exogenous monetary policy shocks to analyze the transmission of monetary shocks to changes in mortgage rates for banks in concentrated markets. Through these methodological approaches, the study effectively considers the influence of macroeconomic conditions, geographical variations, and online competition dynamics, providing a comprehensive understanding of the factors shaping mortgage rate transmission and competition among different types of banks.

4 Monetary policy transmission to average mortgage rates

In this section, I compare the pass-through of monetary policy to mortgage rates by shadow and traditional banks. Then I investigate differences in their transmission of monetary shocks to mortgage rates by lenders operating in highly concentrated markets.

4.1 Comparison between shadow and traditional banks transmission

I compare how different types of lenders transmit monetary policy shocks to mortgage rates by running the following regression for each bank type:

$$R_{bmt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 \mathbb{1} Lender_{kmt} + \beta_3 \mathbb{1} Lender_{kmt} \times \Delta i_t + \epsilon_{kmt} \tag{1}$$

where R_{bmt} is a residualized mortgage rate at bank b in MSA m in quarter t; α_b is bank fixed effect; α_m is MSA fixed effect; $Lender_{kmt}$ is an indicator for traditional banks, FinTech lenders, or non-FinTech lenders; and Δi_t is the monetary policy shock from Bauer and Swanson (2023). I cluster standard errors at the bank level to allow for bank correlation. In a separate regression, I also cluster standard errors at the bank by year-quarter level to allow for time correlations. I find the same outcome, so I do not report them.

Table 2 shows that traditional banks transmit monetary policy shocks by 2 bps marginally less than other lenders. There is no economically significant difference between different types of financial institutions. Both shadow and traditional banks, despite their contrasting operational characteristics—with shadow banks benefiting from reduced regulatory constraints and advanced technology, which typically fosters more efficient and cost-effective loan issuance compared to traditional banks—exhibit similar patterns in transmitting monetary policy shocks to mortgage rates.

Importantly, these results remain robust even after controlling for supply factors, as indicated by the inclusion of bank fixed effects and the interaction of bank-specific factors with year fixed effects. I do not report the interaction between bank and year fixed effects in this paper because they yield the same result. This suggests that both traditional and shadow banks demonstrate a similar transmission of monetary shocks to mortgage rates.

Table 2: Monetary policy transmission

	(1)	(2)	(3)
		Residualized mortgage rate	
Traditional $\times \Delta i_t$	-1.951***		
	(0.568)		
FinTech$\times \Delta i_t$		0.365	
		(0.903)	
Non-FinTech$\times \Delta i_t$			3.019***
			(0.469)
R^2	0.032	0.030	0.033
F	133.2	31.14	76.91
N	18260524	18260524	18260524

Notes: Results from estimating

$$R_{bmt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 \mathbb{1} Lender_{kmt} + \beta_3 \mathbb{1} Lender_{kmt} \times \Delta i_t + \epsilon_{kmt}$$

where R_{bmt} is a residualized mortgage rate at bank b in MSA m in quarter t; α_b is bank fixed effect; α_m is MSA fixed effect; $Lender_{kmt}$ is an indicator for traditional banks, FinTech lenders, or non-FinTech lenders; and Δi_t is the monetary policy shock from Bauer and Swanson (2023) as described in Equation 1. The results are robust after controlling for bank FEs, MSA FEs, interaction between bank and year FEs, and interaction between MSA and year FEs. Standard errors are clustered at the bank level for correlation within banks. Results were similar for standard errors that are clustered at the bank by year-quarter level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

4.2 Importance of market concentration across banks

Given the rapid growth of shadow banks and their increasing online presence, it is important to assess the impact of this growth on regional competition with traditional banks in the mortgage market. Corbae et al. (2023) document that there has been an increasing trend in mortgage market concentration by banks. One potential channel for the difference in pass-through by banks is the competitiveness of the banking markets. In this section, I compare how lenders in highly concentrated markets transmit monetary policy shocks to mortgage rates. Compared to Equation

1, I now introduce a triple interaction with the measure of market concentration:

$$\begin{aligned} R_{bmt} = \alpha_b + \alpha_m + \beta_1 \Delta i_t + \beta_2 \mathbb{1} Lender_{kmt} + \beta_3 \mathbb{1} Lender_{kmt} \times \Delta i_t \\ + \beta_4 HHI_{mt} + \beta_5 HHI_{mt} \times \Delta i_t + \beta_6 \mathbb{1} Lender_{kmt} \times HHI_{mt} \\ + \beta_7 \mathbb{1} Lender_{kmt} \times HHI_{mt} \times \Delta i_t + \epsilon_{mbt} \end{aligned} \tag{2}$$

where the term HHI_{mt} is the local mortgage market concentration in MSA m in quarter t, capturing bank concentration changes over time. I cluster standard errors at the bank level for correlation within banks. In a separate regression, I also cluster standard errors at the bank by year-quarter level to allow for time correlations, but I do not report them because they yield the same outcome.

Table 3 shows that within highly concentrated markets, traditional banks transmit monetary shocks to mortgage rates by 25 bps less, whereas shadow banks transmit 35 bps more. This result highlights the significance of market power within the banking industry and its role in shaping the effectiveness of monetary policy transmission to credit markets. Benetton and Fantino (2021) and Enkhbold (2023) find that market power in traditional banking decreases the transmission of monetary policy to credit. Traditional banks, as opposed to shadow banks, borrow deposits at rates that are both low and unaffected by changes in the policy rate. However, sustaining a deposit franchise entails substantial costs associated with branch maintenance and advertising campaigns. Deposit franchise requires banks to invest in long-term assets to finance short-term deposits. On the contrary, shadow banks rely on investor funding and invest in information technology, which results in a more responsive pass-through mechanism within the mortgage market.

Shadow banks rely on mortgage securitization and investor funding, which makes them more responsive to changes in monetary policy. When the Federal Reserve intervenes by purchasing securities, it has the effect of decreasing the available supply of these securities in the market. This reduction in supply leads to an increase in the prices of these securities and, consequently, a decrease in their yields. Furthermore, in response to the lower yields on US Treasury securities, private investors shift their focus toward acquiring assets with higher yields, including corporate bonds and other privately issued securities. The increased demand from investors for these higher-yielding assets, in turn, results in higher prices for such securities and a subsequent reduction in their yields. Thus, they transmit monetary shocks more to mortgage rates.

Shadow banks are technologically advanced, hence they can adjust their supply more elastically than traditional banks. This is due to their ability to leverage IT to improve their ability to process information and change prices in response to changes in costs (Modi et al., 2022; Fuster et al., 2019). IT investments are often linked to higher firm market power (Berg et al., 2022). FinTech can expedite loan processing (Fuster et al., 2019) and enhance customer convenience (Buchak et al., 2018b). High IT firms cultivate customer loyalty through the convenience they offer. This loyalty, in turn, makes their customer base less responsive to price fluctuations. As a result, a supply shift to changes in costs would lead to a larger change in prices.

Table 3: Market concentration

	(1)	(2)	(3)
		Residualized mortgage rate	
Traditional $\times\Delta i_t\times$HHI	-25.15**		
	(10.68)		
FinTech$\times\Delta i_t\times$HHI		35.73**	
		(17.49)	
Non-FinTech$\times\Delta i_t\times$HHI			36.78**
			(15.34)
R^2	0.276	0.194	0.225
F	8.723	12.58	8.869
N	377429	377429	377429

Notes: Results from estimating

$$R_{bmt} = \alpha_b + \alpha_m + \beta_1\Delta i_t + \beta_2\mathbb{1}Lender_{kmt} + \beta_3\mathbb{1}Lender_{kmt} \times \Delta i_t + \beta_4 HHI_{mt} + \beta_5 HHI_{mt} \times \Delta i_t + \beta_6\mathbb{1}Lender_{kmt} \times HHI_{mt} + \beta_7\mathbb{1}Lender_{kmt} \times HHI_{mt} \times \Delta i_t + \epsilon_{mbt}$$

where R_{bmt} is a mortgage rate at bank b in MSA m in quarter t, α_b is bank fixed effect, and α_m is MSA fixed effect. The term Δi_t is the monetary shock from Bauer and Swanson (2023) as described in Equation 2. $Lender_{kmt}$ is an indicator for traditional banks, FinTech lenders, or non-FinTech lenders. The term HHI_{mt} is the local mortgage market concentration in MSA m, quarter t, capturing bank concentration changes over time. Standard errors are clustered at the bank level for correlation within banks. Results were similar for standard errors that are clustered at the bank by year-quarter level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

5 Heterogeneous monetary transmission to the mortgage rate distribution

I use quantile regression to investigate how banks in highly concentrated markets transmit monetary policy shocks 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 when dealing with data that are skewed, multimodal, or contain outliers, as the traditional approach of examining the conditional mean may not capture the full extent of the patterns observed in the data. I re-estimate Equation (2), but now use a quantile regression technique:

$$\begin{aligned} Q(R_{bmt}) = \alpha_b + \alpha_m + \beta_1^q \Delta i_t + \beta_2^q \mathbb{1}Lender_{kmt} + \beta_3^q \mathbb{1}Lender_{kmt} \times \Delta i_t \\ + \beta_4^q HHI_{mt} + \beta_5^q HHI_{mt} \times \Delta i_t + \beta_6^q \mathbb{1}Lender_{kmt} \times HHI_{mt} \\ + \beta_7^q \mathbb{1}Lender_{kmt} \times HHI_{mt} \times \Delta i_t + u_{bmt}^q \end{aligned} \tag{3}$$

where R_{bmt}^q is the residualized mortgage rate for bank b in MSA M for every quarter t, and Δi_t is the monetary policy shock for a quantile q. I plot β_7 to show how each lender in highly concentrated markets transmits monetary policy to mortgage rates in Figure 3.

Figure 3 shows the average OLS results in red solid lines with confidence intervals in red dashed lines. It also shows quantile regression results in black dots with confidence intervals in the grey area. Figure 3 shows that the transmission is different across the percentiles of the distribution of mortgage rates. Banks are dividing the market, where non-FinTech lenders target the bottom 10% of mortgage rate distribution, traditional banks focus on the 20th to 80th percentiles of mortgage rate distribution, and FinTech lenders compete with traditional banks in the top 10% of mortgage rate distribution by transmitting monetary shocks marginally the least to mortgage rates.

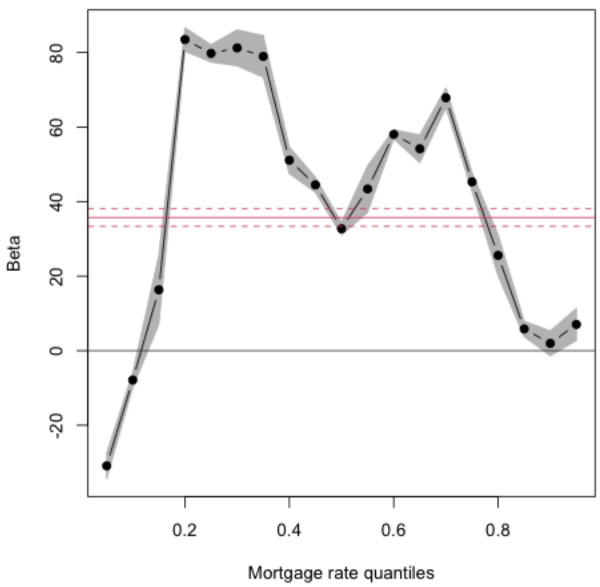
First, I uncover an M-shaped relationship in how monetary policy affects mortgage rates for FinTech lenders operating in highly concentrated markets. For the *lower mortgage rate distribution*, Figure 3a and 3b show that FinTech and non-FinTech lenders in highly concentrated markets transmit monetary policy shock the least to the bottom 10% of mortgage rates. FinTech lenders transmit marginally 25 bps less, while non-FinTech lenders pass-through marginally 40 bps less to mortgage rates. Shadow banks are transmitting the least to the lowest 10% of the mortgage rates and they are entering this market to function as residual lenders. On the contrary, traditional banks in highly concentrated markets are transmitting monetary shocks by 20 to 40 bps more to mortgage rates in the bottom 10th percentile (3c). Since traditional banks already have market shares at the bottom of the mortgage market distribution, they are passing costs to mortgage rates more.

Second, I uncover a U-shaped relationship of monetary policy transmission to mortgage rates for traditional banks in highly concentrated markets. Competition leads to lower transmission to mortgage rates between the 20th and 80th percentiles. For the *middle mortgage rate distribution*, Figure 3c reveals a pattern wherein traditional banks in highly concentrated markets exhibit the lowest transmission rates to borrowers falling within the 20th to 95th percentiles of mortgage rates. Traditional banks transmit monetary shocks by 40 bps less, while both types of shadow banks transmit monetary shocks by 40 to 80 bps more in this range. This counterintuitive transmission behavior can be attributed to the presence of alternative options available to borrowers within this mortgage rate range. Traditional banks, seeking to maintain their market share, absorb the increased funding costs themselves rather than passing them on to borrowers, resulting in reduced transmission.

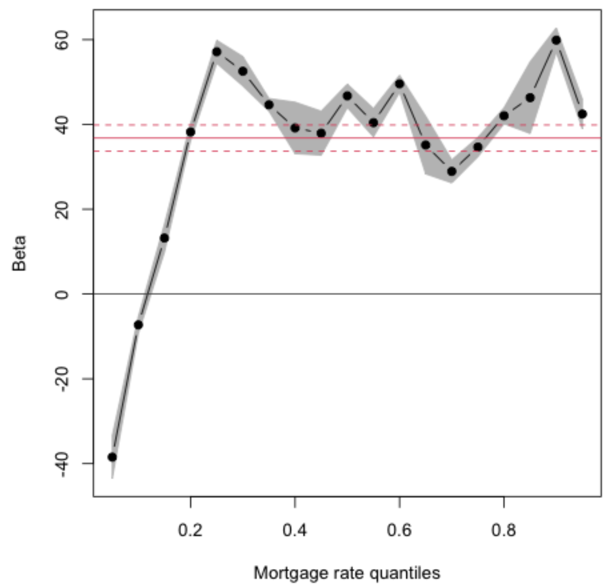
For the *upper mortgage rate distribution*, Figure 3a and 3c demonstrate that only in the 90th to 95th percentile range do FinTech lenders compete with traditional banks, transmitting mortgage rates at similar levels. On the contrary, Figure 3b shows that non-FinTech lenders transmit 40 bps more to mortgage rates without competing with other lender types.

Figure 3: Heterogenous monetary policy transmission

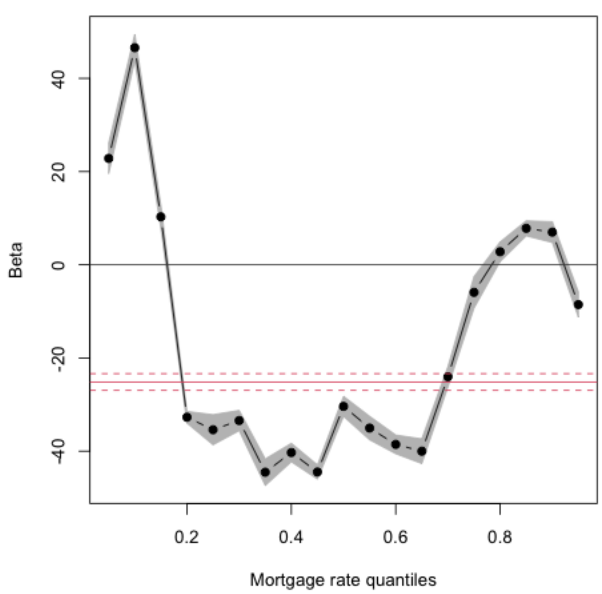
(a) FinTech Lenders



(b) Non-FinTech Lenders



(c) Traditional Banks



Notes: Results from estimating $Q(R_{bmt}) = \alpha_b + \alpha_m + \beta_1^q \Delta i_t + \beta_2^q \mathbb{1} Lender_{kmt} + \beta_3^q \mathbb{1} Lender_{kmt} \times \Delta i_t + \beta_4^q HHI_{mt} + \beta_5^q HHI_{mt} \times \Delta i_t + \beta_6^q \mathbb{1} Lender_{kmt} \times HHI_{mt} + \beta_7^q \mathbb{1} Lender_{kmt} \times HHI_{mt} \times \Delta i_t + u^q_{\theta bmt}$, where R^q_{bmt} is the mortgage rate for bank b in MSA m for every quarter t, and Δi_t is the monetary policy shock for a quantile q as described in Equation 3. I plot β_7 to show how each lender in highly concentrated markets transmits monetary policy to mortgage rates. OLS results are shown in red solid lines with confidence intervals in red dashed lines; quantile regression results are shown in black dots with confidence intervals in the grey area.

6 Theoretical considerations

To explain the results from quantile regression, I present a simple model to illustrate how competition may increase mortgage rate differences between some lenders while decreasing mortgage rate differences between others. The intuition that drives results is similar to Borenstein (1985), which is explored further in Holmes (1989). The competition on price differentials depends on whether price discrimination is based on differences in borrowers' tendency to drop out of the market or their tendency to switch suppliers.

Consider a scenario where three distinct banks operate. These banks can engage in third-degree price discrimination by setting separate mortgage rates. The demand for each bank's mortgage is characterized by elasticity, which can be broken down into two components: an industry-elasticity component and a cross-price elasticity component. For each lender type $i = \{T, F, NF\}$ where T is traditional banks, F is FinTech lenders, and NF is Non-FinTech lenders, the elasticity of demand is given by:

$$e_i(r_i^M) = e_i^I(r_i^M) + e_i^C(r_i^M). \tag{4}$$

Here, e^I, the industry elasticity, measures how responsive aggregate industry demand is to changes in mortgage rates, while e^C, the cross-price elasticity, measures the impact on one bank's demand from changes in the other bank's mortgage rates, and r_i^M is the mortgage rate for each lender type i. Holmes (1989) then shows how the familiar inverse elasticity pricing rule determines equilibrium mortgage rates:

$$\frac{r_i^M - mc}{r_i^M} = \frac{1}{e(r_i^M)} = \frac{1}{e_i^I(r_i^M) + e_i^C(r_i^M)} \tag{5}$$

where mc is the marginal cost assuming all lender types have the same marginal cost. As Holmes (1989) points out, this expression shows that, in a symmetric oligopoly, price discrimination can be based on differences in industry-demand elasticity and/or differences in cross-price elasticities.

I extend the two-type model from Stole (2007) to consider the possibility that lenders differ in terms of borrowers. I illustrate the intuition using a simple three-type model. Table 1 shows that FinTech lenders target borrowers who would like to refinance and who value convenience. As a result, they have a larger fraction of borrowers with a high willingness-to-pay for convenience (Fuster et al., 2019). Non-FinTech lenders have a higher share of borrowers with larger unpaid principal balances. As a result, these borrowers have a high willingness-to-switch (Buchak et al., 2018b). Finally, there are traditional banks that target first-time home buyers, and they are usually price sensitive. Motivated by those empirical regularities, I now turn to three different sets of assumptions that can rationalize my three empirical results from the quantile regression for different ranges of the mortgage rate distribution.

Empirical result 1: FinTech lenders compete with traditional banks for the highest rates. To rationalize this result, I assume traditional banks and FinTech lenders have the same industry elasticity of demand shown in

$$e_T^I = e_F^I > e_{NF}^I. \tag{6}$$

According to the standard inverse elasticity rule, mortgage rate pricing for each bank i is

$$\frac{r_i^M - mc}{r_i^M} = \frac{1}{e_i^I}. \tag{7}$$

Given Equation (6), this implies that $r_T^M = r_F^M < r_{NF}^M$, where traditional banks and FinTech lenders transmit equally but lower than non-FinTech lenders shown in the *upper distribution* of mortgage rates in Figure 3. Under this assumption, the cross-price elasticity is zero because the bank's elasticity is the same as the industry elasticity, implying a monopolist case. Non-FinTech lenders' low industry elasticity means that they can transmit very high to mortgage rates under a monopoly. In contrast, traditional banks' and FinTech lenders' high industry elasticity means that both of them cannot transmit very high to mortgage rates even under monopoly, so competition does not impact their rates as much.

Empirical result 2: Traditional banks primarily target the middle of the mortgage rate distribution. To rationalize this result, I consider traditional banks and FinTech lenders to have the same industry elasticity but have strictly greater cross elasticity of demand than non-FinTech lenders:

$$e_T^I = e_F^I >> e_{NF}^I \tag{6'}$$

and traditional banks and FinTech lenders differ only in their cross elasticity:

$$e_T^C = e_{NF}^C > e_F^C. \tag{8}$$

Using technology-based lending, FinTech lenders can screen potential borrowers better and offer better products than non-FinTech lenders.

Under those assumptions, each bank sets a mortgage rate according to the standard inverse elasticity rule

$$\frac{r_i^M - mc}{r_i^M} = \frac{1}{e_i^I + e_i^C}. \tag{9}$$

The cross elasticities of demand become relevant when there is competition. Equations (6′) and (8) imply $r_T^M < r_{NF}^M < r_F^M$, where traditional banks transmit the least followed by non-FinTech lenders, and FinTech lenders pass-through the highest to mortgage rates shown in the *middle distribution* of mortgage rates in Figure 3. The strictly greater sign in Equation (6′) ensures that FinTech lenders offer mortgage rates higher than those of non-FinTech lenders due to their technological capability to engage in borrower-specific pricing strategies that non-FinTech lenders lack. Figure 3 shows that non-FinTech lenders' low industry elasticity but high cross elasticity means that they cannot transmit very high to mortgage rates when there is competition. In contrast, traditional banks' high industry and cross elasticity means traditional banks cannot transmit very high to mortgage rates even under monopoly, and so competition does not impact their rates as much. FinTechs' low cross elasticity means that they can transmit high to mortgage rates even under competition, and so competition also does not impact their rates as much.

Empirical result 3: Non-FinTech lenders specialize in the lowest rates by transmitting monetary policy the least. To rationalize this result, I assume that Equation (6) still holds but with a new assumption where traditional banks and FinTech lenders have the same industry elasticity and differ only in their cross elasticity:

$$e_T^C < e_{NF}^C < e_F^C. \tag{10}$$

Under this new assumption, only competition can impact FinTech lenders' mortgage rates while traditional banks can transmit policy rates highly to mortgage rates. These equality assumptions may not be realistic but are used to illustrate how the different sources of heterogeneity affect the relationship between market structure and mortgage rate differentials.

Under those assumptions, Equations (6) and (10) imply $r_T^M > r_F^M$, where traditional banks pass-through more than FinTech lenders, shown in the *bottom distribution* of mortgage rates in Figure 3.

However, how non-FinTech lenders respond to traditional banks or FinTech lenders is ambiguous because it can take both greater than or less than signs. Thus, we follow empirical results from Section 5 to guide us how non-FinTech lenders respond to traditional banks and FinTech lenders. Figure 3 shows that non-FinTech lenders' low industry elasticity but high cross elasticity means that they can transmit very high to mortgage rates under monopoly but not when there is competition. In contrast, traditional banks' high industry elasticity means traditional banks cannot pass-through very high to mortgage rates even under monopoly, and so competition does not impact their rates as much. High cross elasticity of FinTech lenders means that they cannot transmit high to mortgage rates under competition.

7 Conclusion

In this paper, I analyze the transmission of monetary policy to mortgage rates through the mortgage market concentration channel, focusing on the behavior of traditional and shadow banks. Shadow and traditional banks exhibit only a subtle difference in transmitting monetary policy shocks to mortgage rates. However, in highly concentrated markets, I find that shadow banks transmit marginally 35 bps more because they rely on investor funding that changes promptly with monetary policy surprises. In contrast, traditional banks transmit marginally 25 bps less because running a deposit franchise incurs high operating costs, because they have incentives to hold mortgages to pay deposit franchises that are unaffected by changes in the policy rate.

Traditional and shadow banks cater to different parts of the mortgage rate distribution. I find that shadow banks target the bottom 10% of the mortgage rate distribution by transmitting monetary policy the least, while traditional banks transmit the most to this group of borrowers. However, traditional banks transmit monetary policy shocks the least to the 20th to 80th percentiles of the mortgage rate distribution. Because borrowers in this range have more options to switch between lenders, traditional banks transmit monetary policy less to retain their mortgage market shares by exercising their market power and absorbing the increased cost of funding. Interestingly, FinTech lenders compete with traditional banks in the top 10% of the mortgage rate distribution, such that for this group of borrowers they have a similar transmission of monetary policy shocks.

Then, I revisit the relationship between market structure and price dispersion in the mortgage industry. Building on early theoretical work showing that competition can increase or decrease mortgage rate differences between consumer types, I develop a simple model with three types of borrowers: high willingness-to-switch, high willingness-to-pay, and price sensitive. The theoretical results show that the relationship between competition and mortgage rate dispersion is ambiguous.

Both my theoretical model and empirical results are rooted in a model of third-degree price discrimination, where lenders transmit different mortgage rates to borrowers who are likely to possess different characteristics. Going forward, my results suggest that the growing prevalence of shadow banks will further exacerbate the heterogeneity in the transmission of monetary policy to the mortgage market, even if the pass-through may not change on average. This warrants more research on the possible macroeconomic impact of such heterogeneous monetary policy transmission.

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