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Essays on the Mortgage Market

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Essays on the Mortgage Market

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by

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ABSTRACT OF THE DISSERTATION

Essays on the Mortgage Market

by

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Doctor of Philosophy in Management
University of California, Los Angeles, 2024
Professor Barney P. Hartman-Glaser, Chair

In Chapter 1 of this dissertation, I document a negative impact of operational capacity pressures of mortgage lenders on the pass-through from mortgage-backed securities (MBS) yields to mortgage rates. In the aggregate time series, I find mortgage-rate pass-through decreases by 12.9% significantly when loan processing cycle increases by 3.3 days; In the panel data, I find mortgage rate pass-through decreases by 10% significantly when lender capacity utilization rate increases by one standard deviation. Moreover, using a difference-in-difference regression with staggered treatment, I find mortgage spread keeps decreasing after the authorization of remote online notarization, which facilitates loan origination operations and relieves lender capacity pressures.

In Chapter 2, I continue to explore mortgage rate pass-through in the primary market by first documenting its properties and then using a search model to explain the mechanism. I find the average pass-through from MBS yields to mortgage rates is 85% (imperfectness); Moreover, the pass-through decreases from 93% to 64% when MBS yield shifts from one standard deviation above its median to one standard deviation below its median (rate dependency). By using a search model involving both the mortgage market and the labor market, I highlight the key role of labor market frictions in causing operational capacity

pressures on mortgage lenders and higher markups in mortgage rates, which explains the observed imperfectness and rate dependency of mortgage rate pass-through, as well as the negative impact of lender capacity pressures on mortgage rate pass-through documented in Chapter 1.

In Chapter 3, I examine whether borrowers are more or less satisfied with nonbank mortgage servicers versus bank servicers, given the rising market share of nonbank servicers in the recent decade. The prevalence of nonbank servicers brings benefits such as increasing market competition, promoting technological advances, and lowering capacity pressures in the mortgage market; but also raises supervisory concerns as the regulatory frameworks for nonbank mortgage players are less mature than for traditional banks. Using complaint data filed with the Consumer Financial Protection Bureau (CFPB), I find higher complaint ratios for nonbanks. To provide evidence that this is not driven by unobservable consumer differences, I use the regional variation in bank capital ratios as an instrument for nonbank penetration levels. Regions with higher predicted market shares of nonbanks also have higher complaint ratios, verifying consumers are less satisfied with the services provided by nonbanks.

The dissertation of Wenjing He is approved.

Mark J. Garmaise

Pierre-Olivier Weill

Tyler Stewart Muir

Barney P. Hartman-Glaser, Committee Chair

University of California, Los Angeles

2024

You are the vine and I am the branch. Remaining in you, I bear much fruit; apart from you, I can do nothing.

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CHAPTER 1

Mortgage Rate Pass-Through and Lender Operational Capacity Pressures

1.1 Introduction

Capital markets for mortgage-backed securities (MBS) are created to provide funding for mortgages and lower the borrowing costs of home buyers, yet changes of yields earned by investors in the MBS market are not fully transmitted to mortgage rates paid by borrowers in the primary market. Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013) document a significant widening of primary mortgage spread (the difference between MBS yields and mortgage rates) from 50 bps in 2008 to more than 100 bps in 2012. Scharfstein and Sunderam (2015) show the sensitivity of changes in mortgage rates to changes in MBS yields is significantly less than 1. This imperfect mortgage rate pass-through is concerning because it reduces the effectiveness of monetary policies. For example, the Federal Reserve's large-asset purchase program of Quantitative Easing involves purchasing MBS assets to lower MBS yields and reduce borrower costs[1], whose efficacy depends heavily on the pass-through from MBS yields to mortgage rates (Walentin (2014), Di Maggio, Kermani, and Palmer (2020), Hancock and Passmore (2011)).

The current literature has emphasized the channel of lender market powers in impeding mortgage rate pass-through. Serving as intermediaries between borrowers in the primary market and investors in the secondary market, mortgage lenders originate loans to borrowers at the mortgage rates, pool loans into MBS assets, and sell them to investors at the MBS

[1] https://www.federalreserve.gov/newsevents/pressreleases/monetary20081125b.htm

yields. Scharfstein and Sunderam (2015) estimate a one standard deviation increase in local market concentration of mortgage lenders decreases the pass-through from MBS yields to mortgage rates by 17%. Drechsler, Savov, and Schnabl (2017) Drechsler, Savov, and Schnabl (2017) present a similar channel of market power in the banking sector where banks in more concentrated markets pass through rising interest rates to deposit rates by a less amount, leading to deposits outflows and contracted lending. However, mortgage market has become more national and less locally concentrated in the recent decade, which renders the channel of market power less important. Amel, Anenberg, and Jorgensen (2018) document 57% to 83% of loans are originated by non-local lenders, the share of counties with HHIs above 2500 ranges from 38% down to 14%, and local concentration has an insignificant impact on mortgage rate pass-through.

As the channel of market power becomes less important, the goal of this paper is to highlight another factor that hinders mortgage rate pass-through: lender operational capacity pressures. When interest rates decrease and refinance demand surges, lenders run at higher capacity utilization rates because of frictions in expanding loan processing capacity in the short term, such as outdated technology platforms and higher labor costs. This causes operational capacity pressures and limits lender capabilities to accommodate the rising mortgage demand, resulting in higher mortgage rates.

Before providing empirical evidence for the negative impact of capacity pressures on mortgage rate pass-through, I define mortgage rate pass-through in the primary mortgage market by providing the background that delineates the transmission process of MBS yields to mortgage rates. Essentially, MBS investors provide funding to mortgage lenders and mortgage lenders provide funding to borrowers. As MBS yields, the funding costs for lenders decrease; mortgage rates, the funding costs for borrowers, also decrease accordingly. Therefore, I define mortgage rate pass-through in the primary mortgage market as the sensitivity of changes in mortgage rates to changes in MBS yields, as in Scharfstein and Sunderam (2015).

Under this context, I first provide macro-level evidence for the negative impact of lender capacity pressures on mortgage rate pass-through. I use the aggregate time series of mortgage rates, MBS yields, and days-to-close for mortgage loans to explore the relation between days-to-close and mortgage rate pass-through, where days-to-close is a proxy for lender capacity pressures. Days-to-close counts the average days it takes from mortgage application to closing, which is a commonly used indicator for lender capacity constraints (Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013), Choi, Choi, and Kim (2022)). I find a 100 bps change in MBS yields leads to a 90 bps change in mortgage rates when days-to-close is at its median level over the sample period, and the change decreases by 12.7 bps significantly when days-to-close increases by one standard deviation (3.26 days).

Next, I run a panel regression to explore the impact of lender capacity pressures on mortgage rate pass-through, using refinance-per-worker as a proxy for capacity pressures. Without data access to days-to-close in the panel level[2], I use refinance-per-worker to measure capacity pressures, which is a concept of capacity utilization rate and defined as the number of refinance loans originated by each worker (Sharpe and Sherlund (2016)). I run the panel regression in county and quarter level over the sample period from 2012 to 2019, controlling for local mortgage market concentration, Fintech lender market share, house price levels, homeownership rates, wages, population, education attainment, and population age characteristics. The result shows when refinance-per-worker increases by one standard deviation, mortgage rate pass-through decreases by 10 bps significantly within county and year, given a 100 bps change in MBS yields.

To mitigate the concern caused by mortgage market becoming more national and more loans are originated remotely (Hurst, Keys, Seru, and Vavra (2016), Amel, Anenberg, and Jorgensen (2018)), I run a robustness check by using refinance-per-appraiser in place of refinance-per-worker in the panel regression. Refinance-per-appraiser is the number of refinance loans originated by each licensed real estate appraiser available in the local area. Refinance-per-appraiser less directly measures lender capacity pressure levels, but could still serve as a proxy given the importance of housing appraisal in the mortgage origination process. Moreover, it has two benefits as compared to refinance-per-worker: first, house ap-

[2]Internal researchers at the Federal Reserve System have access to a version of HMDA data which allows the calculation of days-to-close in the panel level.

praisals can only be done locally while loan underwriting may be done remotely so refinance-per-appraisal may better measure local capacity pressures; second: given the significant time and efforts it takes to become a licensed appraiser, it is unlikely for mortgage lenders to affect the number of appraisers in the market. The robustness check gives a similar result, showing mortgage rate pass-through decreases by 6 bps significantly within county and year, given a 100 bps change in MBS yields.

Finally, to identify the causal impact of lender capacity pressures on mortgage rate pass-through, I run a difference-in-difference analysis with staggered treatment over the sample period from 2016 to 2021, where the treatment is passing laws to allow remote online notarizations (RON). Legally authorizing RON is an important step to full digital mortgage lending and the mortgage industry has lobbied governors for passing RON laws for years. RON makes e-signing possible and incentivizes mortgage lenders to invest in technology to digitalize lending, which increases operational efficiency and relieves capacity pressures. Between 2018 and 2021, 14 states passed RON laws at different time points. Leveraging this staggered treatment, I find primary mortgage spreads decreased significantly after authorizing RON. Assuming the timing of passing RON laws is uncorrelated with factors affecting mortgage rates, this provides evidence for the positive impact on mortgage rate pass-through from allowing RON and reducing lender capacity pressures.

Literature and contribution. This paper contributes to the literature examining monetary policy pass-throughs to homeowners' borrowing costs. Hancock and Passmore (2011) find two important channels through which the Federal Reserve's MBS purchase program could lower mortgage rates: improve market functioning and provide clear government backing for Fannie Mae and Freddie Mac. Stroebel and Taylor (2012) examine the quantitative impact of the Federal Reserve's MBS purchase program and find insignificant effects of the program on mortgage spreads after controlling for prepayment and default risk. Di Maggio, Kermani, and Palmer (2020) document the transmission from Quantitative Easing (QE) to the real economy and find QE-eligible mortgage rates fell by 40 bps more than QE-ineligible jumbo mortgage rates during QE1.

Specifically, this paper contributes to the literature investigating the intermediation role of mortgage lenders in the transmission of monetary policies. Because the determination of MBS yields itself is complicated (Boyarchenko, Fuster, and Lucca (2019)), I skip the step of monetary policy transmission to the secondary market and focus on understanding the pass-through from the secondary market (MBS yields) to the primary market (mortgage rates). Papers taking a similar approach include Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013), Scharfstein and Sunderam (2015), Fuster, Lo, and Willen (2017). Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013) document a rising primary mortgage spread and lender revenue from 1995 to 2012. Scharfstein and Sunderam (2015) present empirical evidence that high concentration in the local mortgage market reduces the sensitivity of mortgage rates to MBS yields. Fuster, Lo, and Willen (2017) estimate 142 bps is captured by mortgage lenders as a price of intermediation between 2008 and 2014 and this price increased each year by 30 bps approximately. My paper documents the negative impact of lender operational capacity pressures on the pass-through from MBS yields to mortgage rates.

Several papers document the negative impact of lender capacity constraints in the mortgage market but none of them identifies a causal impact. Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013) raise several factors that could be contributing to the widening primary mortgage spread from 2008 to 2012, including loan putback risk, mortgage servicing rights values, pipeline hedging costs, originator market power, as well as capacity constraints. Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021) provide suggestive empirical evidence that pandemic-related labor market frictions and operational bottlenecks caused higher intermediation markups set by mortgage lenders. Sharpe and Sherlund (2016) present evidence that capacity constraints result in credit rationing in mortgage originations such that it is harder for low to modest credit borrowers to obtain a mortgage. My paper contributes to this literature by providing complementary and stronger evidence through the panel regression and the difference-in-difference identification with staggered treatment regarding RON.

Furthermore, this paper contributes to the literature of price dispersion and search frictions in the mortgage market. Alexandrov and Koulayev (2017) find a consumer may see a spread of 50 bps in posted prices in the mortgage market, controlling for consumer characteristics, property features, and discount points. Bhutta, Fuster, and Hizmo (2020) estimate a gap of 54 bps between the 10th and 90th percentile mortgage rate for borrowers with the same characteristics, applying for identical loans, in the same market, and on the same day. Many papers attribute this price dispersion to a lack of shopping of borrowers, either due to low financial sophistication or high search costs (Gurun, Matvos, and Seru (2016), Ambokar and Samaee (2019), Bhutta, Fuster, and Hizmo (2020), Alexandrov and Koulayev (2017), Agarwal, Grigsby, Hortaçsu, Matvos, Seru, and Yao (2020)). However, this paper indicates difference in lender capacity pressures could also lead to price dispersion in the mortgage market.

The rest of the paper proceeds as follows. Section 2 describes the background of how monetary policy transmits to the mortgage market. Section 3 provides the macro-level empirical evidence for the impact of lender capacity pressures on mortgage rate pass-through. Section 4 presents the panel regression evidence. Section 5 provides the difference-in-difference evidence. Section 6 concludes.

1.2 Background

In this section, I describe the background of how monetary policies are transmitted to the mortgage market, providing the context of this paper which focuses on understanding mortgage rate pass-through in the primary mortgage market.

Amromin, Bhutta, and Keys (2020) categorize the monetary policies transmitted through mortgage market as "conventional" monetary policies and "unconventional" monetary policies. Conventional monetary policies refer to the Fed changing its target federal funds rate (the inter-bank overnight rate), which affects short-term Treasury rates, thus affecting long-term Treasury rates and mortgage rates. Unconventional monetary policies refer to the Fed providing forward guidance to influence the future path of interest rates, as well as purchasing Treasury and MBS securities in large-scale to lower long-term treasury rates and MBS yields directly (Quantitative Easing), thus affecting mortgage rates.

While lowering mortgage rates and supporting the housing market is one of the goals of these monetary policies, it is challenging to cleanly identify the pass-through from these policies to mortgage rates because there are various ways a monetary policy could affect mortgage rates. For example, changes on federal fund rates influence short-term treasury rates, then change long-term treasury rates, and finally affect mortgage rates; large-scale purchases of treasury assets affect long-term treasury rates, then change mortgage rates; large-scale purchases of MBS assets affect MBS yields, then change mortgage rates; large-scale purchases of treasury assets influence treasury rates, then change MBS yields, and finally change mortgage rates, etc. Moreover, different rates move simultaneously and endogenously with each other, as well as with market conditions. For example, feedback loops exist: as the impact transmits from treasury rates to mortgage rates, it could again affect treasury rates (Malkhozov, Mueller, Vedolin, and Venter (2016)); it could also again affect MBS yields as prepayment and default risks change when mortgage rates change.

Given these intertwined impacts among different kinds of interest rates, industry practitioners and researchers decompose mortgage spread (the difference between mortgage rates and treasury rates) into primary mortgage spread and secondary mortgage spread. Primary mortgage spread is the difference between mortgage rates and MBS yields, and secondary mortgage spread is the difference between MBS yields and treasury rates. The former is more influenced by mortgage lenders and borrowers in the primary mortgage market and the latter is more influenced by capital market investors in the secondary mortgage market. Targeting to examine the intermediation role of mortgage lenders, this paper focuses on the primary mortgage spread, or the pass-through from MBS yields to mortgage rates in the primary mortgage market.

The mortgage origination and securitization process from the viewpoint of mortgage lenders helps us understand why mortgage rates move together with MBS yields. Regulatory changes and technological advances have spurred a growth of originate-to-distribute lenders (Buchak, Matvos, Piskorski, and Seru (2018)). As described in Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013), in a typical originate-to-distribute transaction, mortgage lenders originate loans to borrowers at the mortgage rates and pool the loans into MBS assets with coupons that deliver the highest profits when they sell them to the secondary market (best-execution). Prices for MBS bonds across coupons are crucial in determining the originate-to-distribute profits, thus changes in MBS yields are reflected in mortgage rates. For example, when Fed announced the large-asset purchase program, demand for MBS increased, MBS prices increased, and MBS yields decreased. This would increase mortgage origination profits if mortgage rates did not change and loans were sold as MBS bonds with the same coupon rates. However, due to competition between lenders, as MBS yields declined, mortgage rates also declined, and loans were sold into MBS bonds with lower coupons, stabilizing origination profits. Essentially, MBS investors provide funding to mortgage lenders and mortgage lenders provide funding to borrowers. As MBS yields, the funding costs for lenders decrease; mortgage rates, the funding costs for borrowers, also decrease accordingly.

Therefore, I define mortgage rate pass-through in the primary mortgage market as the sensitivity of changes in mortgage rates to changes in MBS yields, as in Scharfstein and Sunderam (2015). Though the intertwined co-movements and feedbacks between rates could lead to a non-100% pass-through from MBS yields to mortgage rates, I expect this noise to be negligible, or at least much smaller than the observed gap in the empirical pass-through from 100%. With this assumption, I ignore the feedback loops between MBS yields and mortgage rates, and look at the ultimate sensitivity of changes in mortgage rates to MBS yields to explore the role mortgage lenders play in affecting mortgage rate pass-through in the primary market.

1.3 Macro-Level Regression

In this section, I present macro-level evidence for the negative impact of lender operational capacity pressures on mortgage rate pass-through in the primary mortgage market.

One popular measure of lender capacity pressures is days-to-close (Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013)), which counts the number of days from mortgage application to closing. For example, based on the data from Ellie Mae's Origination Insight

Report, during the COVID-19 period, average days-to-close increased from 46 days in late 2019 to 56 days in late 2020 as lenders experienced severe capacity constraints caused by surging demand, labor shortage, and national lock-downs. Unfortunately, only national-level data for days-to-close is publicly available. Therefore, I start from a macro-level analysis using aggregate time series for days-to-close to measure lender capacity pressure levels and run the following regression to explore the relation between mortgage rate pass-through and lender capacity pressures in the national level:

$$\Delta\text{Mortgage Rate}_t = \alpha + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative Days-to-Close}_t + \varepsilon_t \tag{1.1}$$

where ΔMortgage Rate$_t$ is the quarterly change of mortgage rate for a 30-year fixed rate mortgage, ΔMBS Yield$_t$ is the quarterly change of the current coupon rate of Fannie Mae's 30-year MBS, and Relative Days-to-Close is the difference between days-to-close at quarter t and the median days-to-close over the sample period from 2012 to 2019. I use relative days-to-close in the regression so the estimate of coefficient β_1 can be interpreted as the pass-through from MBS yields to mortgage rates when days-to-close is at its median level. β_2 measures the marginal impact on mortgage rate pass-through when days-to-close increases by 1 day.

1.3.1 Data

Data for mortgage rates is from Freddie Mac's Primary Mortgage Market Survey, which gathers inputs from lenders on their first-line prime conventional confirming 30-year fixed rate home purchase mortgages. Data for MBS yields is from the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. Data for Days-to-Close is from Ellie Mae's Origination Insight Report, which summarizes average days-to-close based on a robust sample of mortgage applications across the country that uses Ellie Mae's Encompass mortgage management platform. Ellie Mae's Encompass is an industry leading lending software, with a wide customer base of lenders and investors. For example, in 2014, among the total 10 million mortgage applications, approximately 3.7 million applications ran through Ellie Mae's

Encompass[3].

Table 1.1 presents the summary statistics. From 2012 to 2019, 30-year mortgage rate has a mean of 3.97% and a standard deviation of 36 bps; MBS yield has a mean of 2.99% and a standard deviation of 42 bps; the quarterly change of mortgage rate ranges from a negative 41 bps to a positive 76 bps, with a standard deviation of 25 bps; the quarterly change of MBS yield ranges from a negative 47 bps to a positive 76 bps, with a standard deviation of 29 bps; average days-to-close has a mean of 44.6 days and a standard deviation of 3.3 days.

1.3.2 Result

Table 1.2 shows the regression result. The second row shows mortgage rate pass-through is 89.7% when days-to-close is at its median; The fourth row shows mortgage rate pass-through decreases by 12.9% significantly when days-to-close increases by one standard deviation (3.3 days). This result is both statistically and economically significant. For example, during the COVID-19 period from 2019Q4 to 2020Q3, days-to-close increased by 10 days and MBS yield decreased by 132 bps. Based on the regression result, mortgage rate pass-through was predicted to decrease by 39% and primary mortgage spread was predicted to increase by 51.5 bps.[4] For a 30-year mortgage loan with a balance of $300K, when mortgage rate increases by 50 bps from 3.5% to 4.0%, the monthly payment increases by $125 (a 14% increase) and the total future value of the loan increases by $138K (a 25% increase). This significant negative correlation between days-to-close and the sensitivity of mortgage rates to MBS yields in the national level provides suggestive evidence for the negative impact of lender capacity pressures on mortgage rate pass-through.

[3] Ellie Mae's 2014 Origination Insight Report.

[4] This is similar to the actual increase of 57 bps in mortgage spread during this period.

1.4 Panel Regression

In this section, I present panel regression evidence for the negative impact of lender operational capacity pressures on mortgage rate pass-through in the primary mortgage market.

Taking a similar approach as in Scharfstein and Sunderam (2015), I run the following regression:

$$\begin{aligned} \Delta\text{Residual Rate}_{k,t} =& \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Refinance-Per-Worker}_{k,t} \\ & + \Gamma X_{k,t} + \nu_k + \xi_t + \varepsilon_{k,t} \end{aligned} \tag{1.2}$$

where ΔResidual Rate$_{k,t}$ is the average change of residual mortgage rate in county k over quarter t after purging the impact of loan credit scores (FICOs) and loan-to-value ratios (LTVs), ΔMBS Yield$_t$ is the change of MBS yield over quarter t, and Refinance-Per-Worker$_{k,t}$ is the number of refinance loan originations[5] in county k and quarter t divided by the number of workers in the mortgage industry in county k and quarter $t-1$. Scharfstein and Sunderam (2015) explore the impact of lender market powers and use local market concentration as the focal variable. Here I include local market concentration as one control variable and use refinance-per-worker as the focal variable to explore the impact of lender capacity pressures on mortgage rate pass-through.

Since days-to-close is only available in the national level, I use refinance-per-worker instead of days-to-close to indicate for capacity pressure levels in the panel regression. Refinance-per-worker measures capacity utilization and higher capacity utilization rate implies stronger capacity pressures. $X_{k,t}$ include three sets of controls. The first set are variables documented to have potential impacts on mortgage rates, including local market concentration (Scharfstein and Sunderam (2015)) and fintech lender market share (Fuster, Plosser, Schnabl, and Vickery (2018)). The second set of controls are variables closely related to the housing market, including housing price levels, homeownership rates, and wages. The

[5] I use refinance loan originations instead of all originations to avoid the seasonal noise from the purchase originations.

third set of controls are county characteristics, including total population, population share of black people, population share of people younger than 19, population share of people older than 65, and population share of people with a Bachelor's degree or higher. ν_k is county fixed effect, which controls for time-invariant regional characteristics. ξ_t is quarter fixed effect, which controls for common macro trends across regions. In the regression, total mortgage rate pass-through is measured by ($\beta_1 + \beta_2$Refinance-Per-Worker) and β_2 is the impact of lender capacity pressures, after controlling for common macro trends, time-invariant regional characteristics and the three sets of controls which could vary by both time and region.

1.4.1 Data

In the panel regression, data for mortgage rate comes from Fannie Mae's Loan Performance dataset, which provides loan-level data for all the 30-year and less, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages acquired by Fannie Mae, including rich information such as loan characteristics, property information, borrower information, and historical performance. As in Scharfstein and Sunderam (2015), I only include data for 30-year refinance loans with a FICO score above 660 to start with a sample of similar loans. Then to calculate residual rates, I run the following regression each quarter to purge the effects of observable FICOs and LTVs:

$$\text{Mortgage Rate}_{it} = \beta_{0t} + \beta_{1t}\text{FICO Bucket}_i + \beta_{2t}\text{LTV Bucket}_i + \varepsilon_{it} \tag{1.3}$$

where Mortgage Rate_{it} is the mortgage rate for loan i originated in quarter t. FICO Bucket_i is a series of FICO dummies (660-679, 680-699, ...), with 740-759 as the reference bucket. LTV Bucket_i is a series of LTV dummies (50-54,55-59,...), with 70-74 as the reference bucket. Then the residual rate of loan i is $\beta_{0t} + \varepsilon_{it}$, which purges the rate variation due to observable FICOs and LTVs, and is a hypothetical rate for the loan if it had a FICO score within 740-759 and LTV within 70-74.

Data for refinance-per-worker comes from Fannie Mae's Loan Performance dataset and the BLS Quarterly Census of Employment and Wages (QCEW) program. Using Fannie Mae's Loan Performance dataset, I calculate the number of all the refinance loans acquired by Fannie Mae in each county and quarter.[6] Using the QCEW dataset, I obtain the employment level in the private sector for the real estate credit industry for each county and quarter. I use the ratio of these two to estimate refinance-per-worker. To avoid endogeneity bias related to contemporary lender decisions, I use the employment level in the previous quarter to calculate refinance-per-worker.

MBS yields are approximated by the current coupon rates of 30-year Fannie Mae MBS downloaded from Bloomberg. To measure local market concentration, I use the Home Mortgage Disclosure Act (HMDA) data to calculate the sum of market shares of top 4 lenders in each county and year. To calculate local fintech lender shares, I use the HMDA data and the fintech lender classification data from Fuster, Plosser, Schnabl, and Vickery (2018). Housing price levels are from Zillow Home Value Index, which measures the value of a typical home across regions, housing types and time. Average wages are from the BLS QCEW program. Homeownership rates, population characteristics, and education attainment data are from the US Census.

The final sample includes 4,463 data points, covering 144 counties and 31 quarters from 2012 to 2019. Table 1.3 reports the summary statistics. The first line shows the average residual rate ranges from 3.41% to 5.59%, with a mean of 4.31% and a standard deviation of 40 bps. The second line shows on average the quarterly changes of residual rate is almost zero, but the change varies from a negative 66 bps to a positive 89 bps, with a standard deviation of 26 bps. The fourth line shows the average change of MBS yield is about zero, but the change varies from a negative 47 bps to a positive of 76 bps, with a standard deviation of 28 bps. The sixth line shows the average refinance-per-worker is 0.6, with a standard deviation of 0.6. This is smaller than the actual number of all the refinance loans a worker processes each quarter due to the approximation of using acquisition data from Fannie Mae. However, there is a good variation in the approximated refinance-per-worker,

[6] Ideally, I would use the number of all the refinance originations instead of acquisitions by Fannie Mae. But due to data availability, I use the latter as an approximation.

as well as a high correlation between it and days-to-close in the aggregate level, corroborating its validity as an indicator for lender capacity pressures. The last ten rows show summary statistics for the control variables, including the local market concentration measured by the sum of top 4 lender shares, fintech lender market shares, house prices, average wages, homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher.

1.4.2 Result

Table 1.4 summarizes the result of the panel regression: Column (2) is the main result, which includes all the controls, as well as year and county fixed effects; Column (1) excludes the controls; Column (3) excludes the year fixed effect; Column (4) excludes the county fixed effect; Column (5) excludes both the county and year fixed effects. Coefficients and standard errors clustered by county and year are reported. The third row shows the result for our coefficient of interest β_2, which measures the impact of capacity pressures on mortgage rate pass-through. The main result in Column (2) says when refinance-per-worker increases by one standard deviation (0.6), mortgage rate pass-through decreases by 10% within county and year, holding market concentration, fintech share, house prices, wages, homeownership rates, population characteristics, and education attainment constant. This significant negative impact of lender capacity pressures on mortgage rate pass-through holds robustly across all the columns. To illustrate the magnitude of the economic impact, consider the case when MBS yield decreases by 100 bps. A perfect pass-through would lead to a decrease of mortgage rate by 100 bps, while a one standard deviation increase in refinance-per-worker would lead to a loss of 10 bps in the pass-through. For a 30-year fixed rate mortgage loan with a balance of \$300K, when mortgage rate increases by 10 bps from 3.5% to 3.6%, the monthly payment increases by \$25 (a 3% increase) and the total future value of the loan increases by \$26K (a 5% increase).

1.4.3 Robustness

One may be concerned about using refinance-per-worker to measure lender capacity pressure levels locally for three reasons. First, the mortgage market has become more national due to the redistribution effect of the GSEs[7] (Hurst, Keys, Seru, and Vavra (2016)). Second, as technology advances, more loans are originated online by non-local lenders (Amromin, Bhutta, and Keys (2020)). Third, the size of workforce is determined by mortgage lenders endogenously, which might be correlated to other factors affecting mortgage rates, such as technological efficiency (Fuster, Plosser, Schnabl, and Vickery (2018)). To mitigate these concerns, I run a robustness check by using refinance-per-appraiser instead of refinance-per-worker to proxy for lender capacity pressure levels:

$$\begin{aligned}\Delta\text{Residual Rate}_{k,t} =& \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Refinance-Per-Appraiser}_{k,t} \\ &+ \Gamma X_{k,t} + \nu_k + \xi_t + \varepsilon_{k,t} \end{aligned} \tag{1.4}$$

where Refinance-Per-Appraiser$_{k,t}$ is the number of refinance originations in county k and quarter t divided by the number of licensed residential real-estate appraisers in county k and the previous year of quarter t.

Housing appraisal is an important step in the mortgage application process, through which the fair market value of a home is determined. A house appraisal can take anywhere between a few days to several weeks, depending on factors such as the type of appraisal, the laws of the state, and the house condition. To become a house appraiser, you need to complete hundreds hours of coursework, apply for a license, and receive thousands hours of training as an appraisal apprentice. Because of an increasing proportion of aging appraisers in the market and a lack of new entrants, there has been a shortage of appraisers in the market: the Appraiser Institute reported a decline of 13% of active appraisers since

[7] The government-sponsored enterprises Fannie Mae and Freddie Mac.

2013.[8] Since a loan could not be closed without the completion of appraisals[9], I expect a higher refinance-per-appraiser to increase lenders' operational capacity pressures. While a loan could be underwritten by remote workers, the housing appraisal has to be done locally, which makes refinance-per-appraiser more relevant in measuring local capacity pressure levels. Furthermore, lenders could hardly affect the number of available licensed appraisers in the market, which removes the endogeneity concern of the correlation between lender characteristics and the workforce.

Data for licensed appraisers is from the National Registry of Appraisers. Table 1.5 reports the summary statistics for the sample data from 2012 to 2019, which includes 12,117 data points, covering 391 counties and 31 quarters. The fifth row shows the number of licensed appraisers in a county has a mean of 91 and a standard deviation of 160. Table 1.6 shows the regression result. The main result is in Column (2), which includes all the controls and fixed effects. Column (2) implies when refinance-per-appraiser increases by one standard deviation (1.8), mortgage rate pass-through decreases by 5.8% within county and year, holding market concentration, fintech share, house prices, wages, homeownership rates, population characteristics, and education attainment constant. In economic terms, when MBS yield decreases by 100 bps, the increase in refinance-per-appraiser by one standard deviation lowers the pass-through to mortgage rates by 6 bps. Compared to the main result using refinance-per-worker, the result using refinance-per-appraiser is smaller in magnitude and less significant. This may be caused by two reasons: first, refinance-per-appraiser is a less direct measure for lender operational capacity pressures than refinance-per-worker; second, the National Registry of Appraisers provides data for all the licensed appraisers but not all of them are actively working in the market. Nevertheless, the result here is consistent with the main result, showing a significantly negative impact of lender capacity pressures on mortgage rate pass-through.

[8] `https://appraisalbuzz.com/how-tech-is-working-on-the-solution-to-the-appraiser-shortage/`

[9] Though some loans could choose the option of appraisal waiver or digital appraisal, most loans still require an in-person appraisal in the sample period from 2012 to 2019. `https://www.aei.org/research-products/report/prevalence-of-gse-appraisal-waivers/`.

1.5 Diff-in-Diff Regression

Both the macro-level regression (Section 1.3) and the panel-level regression (Section 1.4) provide evidence for the negative correlation between lender operational capacity pressures and mortgage rate pass-through. In this section, I provide further evidence to identify this impact causally, using a difference-in-difference regression with staggered treatment regarding passing laws to allow remote online notarization (RON).

A real estate notary plays an important role in the mortgage closing process by walking borrowers through loan documents, ensuring all paperwork are signed correctly, and returning documents to lenders. Allowing RON is a critical step to accomplish a full digital mortgage experience, which could simplify the whole mortgage origination process and alleviate lender operational capacity pressures. Based on a study published by MarketWise Advisors[10] in 2021, digital closings reduce loan processing cycle by 7.16 days on average and save lender cost by $444 per loan[11]. In 2017, Virginia is the only state allowing RON and the Mortgage Bankers Association (MBA) started a campaign to advocate for the passage of RON[12]. Since then, 44 states passed RON laws at different time points. This staggered treatment provides an ideal quasi-random experiment to explore the impact of lender capacity pressures on mortgage rate pass-through, given the following assumptions: (i) the timing difference between states in passing RON laws is random; (ii) RON affects mortgage rates only through reducing lender capacity pressures.

Specifically, I run the following regression for the sample period from 2016 to 2021

$$\text{Residual Spread}_{k,t} = \sum_{i=-36}^{36} \beta_i \times \text{Treat}_{k,t,i} + \Gamma X_{k,t} + \nu_k + \zeta_t + \varepsilon_{k,t} \tag{1.5}$$

Residual $\text{Spread}_{k,t}$ is the average residual mortgage spread for county k and month t, which

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[10]MarketWise Advisors LLC is a financial technology consulting firm focused on the mortgage industry.

[11]`https://www.businesswire.com/news/home/20220208005408/en/Study-Finds-Online-Notarization-Drives-Impactful-ROI-for-Lenders-and-Title-Agents`

[12]`https://www.mba.org/advocacy-and-policy/residential-policy-issues/remote-online-notarization`

is higher when mortgage rate pass-through is worse. Though mortgage rate pass-through is more accurately measured by the sensitivity of mortgage rate changes to MBS yield changes, I use primary mortgage spread here to fit into the difference-in-difference regression specification. Residual mortgage spread is the difference between residual mortgage rate and MBS yield, where residual mortgage rate is the mortgage rate for a hypothetical loan with FICO within 740-759 and LTV within 70-74 as described in Section 1.4. $\text{Treat}_{k,t,i}$ is 1 if county k adopted RON i months before month t and β_i measures the treatment effect of RON at the ith month after its adoption. I estimate the treatment effect for 36 months before and 36 months after the treatment, where month $i = -1$ is the reference period. ν_k is county fixed effect which controls for time-invariant county characteristics. ζ_k is month fixed effect, which controls for common macro time trend, such as increasing mortgage spread nationally during the pandemic period. Similar to the panel regression, I also include a bunch of control variables $X_{k,t}$ that could affect mortgage rate pass-through and vary by county and time, including local market concentration, fintech lender market shares, house prices, homeownership rates, wages, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher.

1.5.1 Data

I collected data for legal authorization dates of remote online notarization from the website of DocuSign[13], one of the largest electronic signature processing companies in the United States. It provides information for the history and current status of remote online notarization (RON) laws for each juridical state. Table 1.7 shows the RON legalization date for states allowing RON as of 2021Q1. Figure 1.1 plots the trend of RON adoption, which shows the number of states allowing RON increases from 3 in 2018Q3 to 25 in 2021Q1.

For other variables in the diff-in-diff regression, I collect the county-month level data from the same data source as described in Section 1.4. Then I merge the RON data with

[13] For example, `https://www.docusign.com/products/notary/legality/alaska`.

the panel data to construct the sample data from 2016 to 2021, which includes 31,465 data points, covering 565 counties and 63 months. 313 counties are in states with RON laws passed at some point during the sample period, and 252 counties are in states that had never authorized RON during the sample period. Table 1.8 reports the summary statistics. The first line shows average residual mortgage spread ranges from 39 bps to 264 bps, with a mean of 140 bps and a standard deviation of 25 bps. The rest rows show summary statistics for the control variables.

1.5.2 Result

Figure 1.2 shows the result of this diff-in-diff regression with staggered treatment of RON over the sample period from 2016 to 2021, using the approach in Sun and Abraham (2021)[14]. Treatment effects (β_i) of RON on mortgage spreads are plotted, where x-axis is the number of months after treatment and y-axis is the difference in residual spread between treated and non-treated counties. The figure shows no pre-trends and a significant decreasing trend after the treatment. Allowing RON reduced residual mortgage spread by more than 5 bps on average in about 18 months after the treatment, and up to 15 bps in 30 months after the treatment.

Assuming the timing difference between states in passing RON laws is random, this result provides causal evidence that allowing remote online notarization reduces primary mortgage spread. Assuming RON affects mortgage rate only through the channel of relieving lender operational capacity pressures, this result supports the negative impact of capacity pressures on mortgage rate pass-through. How does allowing remote online notarization relieve lender capacity pressures? I expect RON itself to have a negligible impact on lender operational efficiency and mortgage spreads, which is consistent with the small impact in Figure 1.2 in the early months after adopting RON. However, as the Mortgage Bankers Association (MBA) emphasizes in their campaign to push the passage of RON laws, allowing RON removes the roadblocks for digital mortgages and stimulates lenders to invest in technology to digitalize

[14]Sun and Abraham (2021) correct the bias due to treatment effect heterogeneity between periods, which is present in the usual two-way fixed effects regressions with leads and lags.

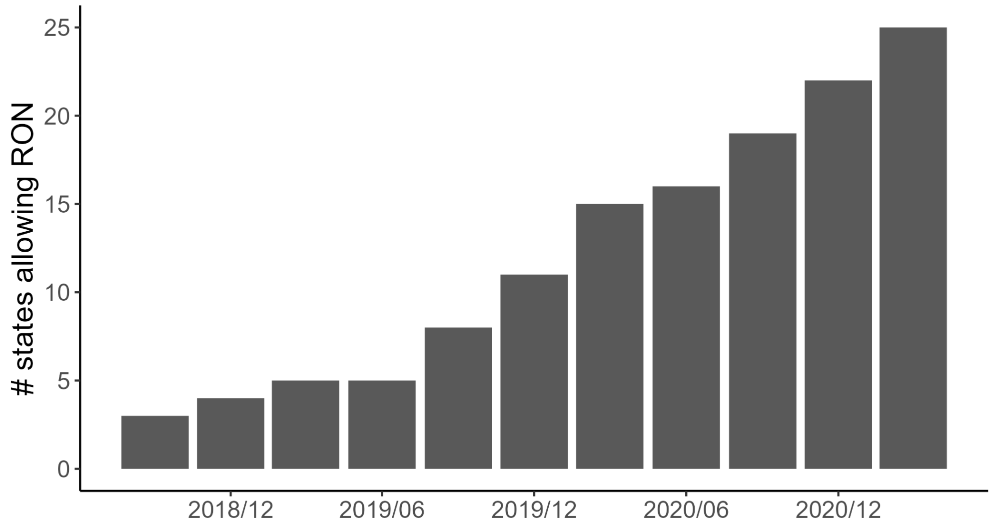
lending and improve operational efficiency. Therefore, as time passes and lenders improve their operation platforms, I expect to see a gradually increasing treatment impact, which is what Figure 1.2 demonstrates. In addition, the benefit of RON and digital mortgage origination is more salient during the COVID-19 period, when it was difficult to obtain real-estate notary signings due to social distancing.

1.6 Conclusion

The rising trend of primary mortgage spread after the financial crisis has caused concerns over the effectiveness of mortgage rate pass-through in the primary market. Different from papers focusing on the market power of mortgage lenders, this paper highlights the important role of lender operational capacity pressures in hindering mortgage rate pass-through in the recent decade. Three pieces of evidence are provided to demonstrate the negative impact of lender capacity pressures on mortgage rate pass-through: a negative correlation between mortgage rate pass-through and the length of loan processing cycle in the macro-level time series data; a negative correlation between mortgage rate pass-through and capacity utilization rate in the panel data; and a decreasing trend of primary spread after the treatment of legally authorizing remote online notarization, which improves lending operational efficiencies.

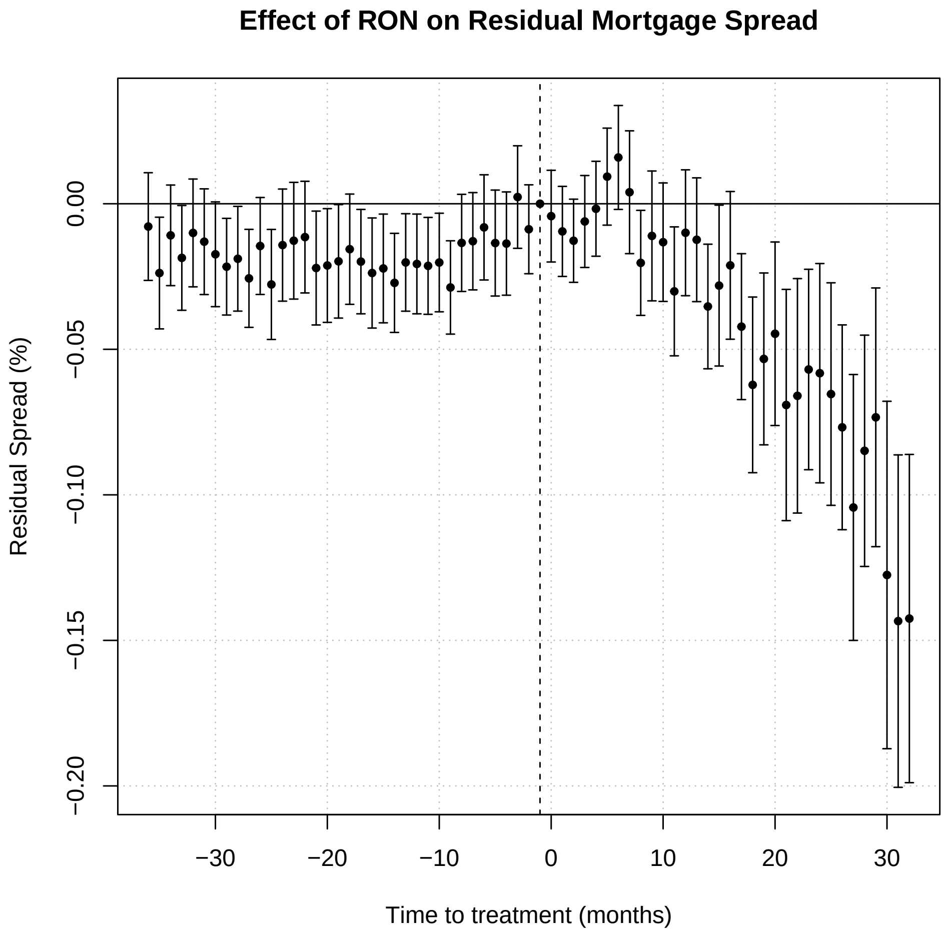
The paper's finding has important implications for policy markers. As mortgage market becomes more national and competitive, market power become less concerning. In contrast, lender operational capacity pressures become more important in hindering the effectiveness of monetary policies. This reminds us of the COVID-19 pandemic, when a surge in mortgage demand and a dive in labor supply happened at the same time, causing significant capacity constraints on mortgage lenders and resulting in a 57 bps rise in primary mortgage spread. Hence, making the mortgage industry scalable in operations is critical in improving the welfare of households. One solution is to accelerate mortgage processing by digitalizing operations, which requires support from policy makers such as encouraging electronic appraisals and accepting digital mortgage records by county offices.

Figure 1.1: Trend of Adopting Remote Online Notarization



This figure shows the total number of juridical states allowing remote online notarization (RON) in each quarter from 2018Q2 to 2021Q1. The data comes from DocuSign's website, which provides information for the history and current status of RON laws in each juridical state. For example, `https://www.docusign.com/products/notary/legality/alaska` gives the information for Alaska.

Figure 1.2: Staggered Treatment of Remote Online Notarization



$$\text{Residual Spread}_{k,t} = \sum_{i=-36}^{36} \beta_i \times \text{Treat}_{k,t,i} + \Gamma X_{k,t} + \nu_k + \zeta_t + \varepsilon_{k,t}$$

This figure shows the result of the above diff-in-diff regression with staggered treatment of allowing remote online notarization (RON) over the sample period from 2016 to 2021, using the approach in Sun and Abraham (2021). Treatment effects (β_i) of allowing RON on mortgage spreads are plotted, where x-axis is the number of months after the treatment date and y-axis is the difference in residual mortgage spread between the treated and non-treated counties. RON treatment data is derived from the history information of RON laws in each juridical state provided by DocuSign's website. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Spread$_{k,t}$ is the gap between average residual rate in county k and month t over MBS yield in month t, where MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. $X_{k,t}$ includes controls of local market concentration, fintech market share, house prices, wages, homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher. ν_k and ζ_t are county and month fixed effects. Standard errors are clustered by county.

Table 1.1: **Summary Statistics (Macro Level Regression)**

	Mean	SD	Min	Q25	Q50	Q75	Max
Mortgage Rate_t(%)	3.97	0.36	3.36	3.71	3.92	4.25	4.78
ΔMortgage Rate_t(bps)	-1	25	-41	-16	-9	13	76
MBS Yield_t(%)	2.99	0.42	2.18	2.70	2.94	3.34	3.88
ΔMBS Yield_t(bps)	-1	29	-47	-17	-6	18	76
Days-to-close_t	44.6	3.3	39.0	42.3	43.3	46.7	53.0

This table shows the summary statistics for the sample data used in the macro-level regression $\Delta\text{Mortgage Rate}_t = \alpha + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative Days-to-Close}_t + \varepsilon_t$. The sample uses quarterly data from 2012 to 2019. Mortgage Rate_t is the average mortgage rate in quarter t from Freddie Mac's Primary Mortgage Market Survey. ΔMortgage Rate_t is the change of mortgage rate from quarter $t-1$ to t. MBS Yield_t is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg in quarter t. ΔMBS Yield_t is the change of the current coupon rate of 30-year Fannie Mae MBS from quarter $t-1$ to t. Days-to-Close_t is the average days-to-close for a mortgage loan from Ellie Mae's Origination Insight Report.

Table 1.2: Mortgage Rate Pass-through and Days-to-Close

Dependent Variable:	ΔMortgage Rate$_t$
Model:	(1)
Constant	0.007
	(0.719)
ΔMBS Yield$_t$	0.897***
	(26.1)
Relative Days-to-Close$_t$	-0.005
	(-1.58)
ΔMBS Yield$_t$ $\times$ Relative Days-to-Close$_t$	-0.039***
	(-3.42)
Observations	31
R^2	0.96322
Adjusted R^2	0.95914

IID co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta\text{Mortgage Rate}_t = \alpha + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative Days-to-Close}_t + \varepsilon_t$$

This table runs the above regression to explore the relation between mortgage rate pass-through and average days-to-close, a measure of lender operational capacity pressures. ΔMortgage Rate$_t$ is the quarterly change of 30-year fixed rate mortgage rate, ΔMBS Yield$_t$ is the quarterly change of the current coupon rate of Fannie Mae's 30-year MBS, Relative Days-to-Close is the difference between days-to-close at quarter t and the median days-to-close over the sample period from 2012 to 2019. β_1 (the second row) measures the pass-through from MBS yields to mortgage rates when days-to-close is at its median level. β_2 (the fourth row) measures the impact of days-to-close on the pass-through from MBS yields to mortgage rates.

Table 1.3: Summary Statistics (Panel Regression)

	Mean	SD	Min	Q25	Q50	Q75	Max
Residual Rate$_{k,t}$(%)	4.31	0.40	3.41	4.03	4.30	4.56	5.59
ΔResidual Rate$_{k,t}$(bps)	-1	26	-66	-17	-4	12	89
MBS Yield$_t$(%)	2.99	0.41	2.18	2.69	2.94	3.39	3.88
ΔMBS Yield$_t$(bps)	-2	28	-47	-23	-8	19	76
Number of Workers$_{k,t}$	896	1501	8	166	377	963	13924
Refinance-Per-Worker$_{k,t}$	0.6	0.6	0.0	0.2	0.4	0.8	4.4
Top 4 Lender Share$_{k,t}$(%)	31.7	8.8	13.3	25.0	30.7	37.2	77.5
Fintech Share$_{k,t}$(%)	6.1	3.4	0.5	3.5	5.9	8.7	19.2
House Price$_{k,t}$(thousands)	242.1	146.0	71.2	155.1	203.9	276.9	1453.5
Wage$_{k,t}$(thousands)	50.8	11.4	27.7	43.4	48.5	55.6	168.5
Homeownership Rate$_{k,t}$(%)	63.0	8.1	29.3	58.9	63.8	68.1	86.3
Population$_{k,t}$(millions)	0.8	1.1	0.1	0.3	0.5	0.9	10.1
Black Share$_{k,t}$(%)	15.8	12.9	0.8	5.5	13.1	22.6	67.8
Younger Than 19 Share$_{k,t}$(%)	25.7	2.8	15.9	24.2	25.6	27.1	39.5
Older Than 65 Share$_{k,t}$(%)	14.3	3.7	6.6	12.1	14.0	15.7	36.7
Bachelor Degree Share$_{k,t}$(%)	32.1	8.3	13.5	27.2	30.9	36.4	59.2

This table shows the summary statistics for the sample used in the panel regression $\Delta\text{Residual Rate}_{k,t} = \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Refinance-Per-Worker}_{k,t} + \Gamma X_{k,t} + \alpha_k + \zeta_t + \varepsilon_{k,t}$. The sample uses quarterly data from 2012 to 2019, including 4,463 data points, covering 144 counties and 31 quarters. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Rate$_{k,t}$ is the average residual mortgage rate of county k and quarter t, after purging the impact of FICOs and LTVs for each loan. MBS yields are the current coupon rates of 30-year Fannie Mae MBS from Bloomberg. Refinance-Per-Worker$_{k,t}$ is the number of refinance loan originations acquired by Fannie Mae in county k and quarter t divided by the number of workers in the mortgage industry in county k and quarter $t-1$, calculated using Fannie Mae's Loan Performance Dataset and the employment data for the real estate credit industry from the BLS QCEW data. Top 4 Lender Share$_{k,t}$ is the total market share of the top 4 lenders ordered by origination volume, based on HMDA data. Fintech Share$_{k,t}$ is the market share of fintech lenders, based on HMDA data and fintech lender classifications in Fuster, Plosser, Schnabl, and Vickery (2018). House Prices$_{k,t}$ is the value of a typical home provided by the Zillow Home Value Index. Wage$_{k,t}$ is the average wage of all industries from the BLS QCEW data. The last ten rows report summary statistics obtained from the U.S. Census data for the following control variables: homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher.

Table 1.4: Mortgage Rate Pass-through and Refinance-Per-Worker

Dependent Variable:	ΔResidual Rate$_t$				
Model:	(1)	(2)	(3)	(4)	(5)
ΔMBS Yield$_t$	0.728***	4.90***	3.89***	5.19***	3.54***
	(0.135)	(1.30)	(0.996)	(1.37)	(0.882)
Refinance-Per-Worker$_t$	-0.124***	-0.131***	-0.137***	-0.061***	-0.071***
	(0.027)	(0.028)	(0.025)	(0.014)	(0.012)
ΔMBS Yield$_t$ $\times$ Refinance-Per-Worker$_t$	-0.149***	-0.161***	-0.182***	-0.132**	-0.146***
	(0.034)	(0.042)	(0.026)	(0.047)	(0.028)
year	Yes	Yes		Yes	
county	Yes	Yes	Yes		
controls		Yes	Yes	Yes	Yes
Observations	4,463	4,463	4,463	4,463	4,463
R^2	0.82366	0.83409	0.80933	0.81532	0.77815
Within R^2	0.59024	0.61448	0.80875	0.57137	

Clustered (county & year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta\text{Residual Rate}_{k,t} = \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Refinance-Per-Worker}_{k,t} + \Gamma X_{k,t} + \nu_k + \xi_t + \varepsilon_{k,t}$$

Using quarterly data from 2012 to 2019, this table runs the above regression to investigate the relation between lender capacity pressures and mortgage rate pass-through, where refinance-per-worker is a proxy for capacity pressures. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Rate$_{k,t}$ is the average residual mortgage rate of county k and quarter t, after purging the impact of FICOs and LTVs for each loan. MBS yields are the current coupon rates of 30-year Fannie Mae MBS from Bloomberg. Refinance-Per-Worker$_{k,t}$ is the number of refinance loan originations acquired by Fannie Mae in county k and quarter t divided by the number of workers in the mortgage industry in county k and quarter $t-1$, calculated using Fannie Mae's Loan Performance Dataset and the employment data for the real estate credit industry from the BLS QCEW data. $X_{k,t}$ includes the following control variables: local market concentration measured by the total market share of top 4 lenders, fintech lender market shares, house prices, wages, homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher. ν_k is the county fixed effect and ξ_t is the year fixed effect. Standard errors are clustered by county and year. The third row shows the impact of lender capacity pressures on mortgage rate pass-through.

Table 1.5: **Summary Statistics (Panel Regression Robustness)**

	Mean	SD	Min	Q25	Q50	Q75	Max
Residual Rate$_{k,t}$(%)	4.30	0.40	3.27	4.01	4.28	4.55	5.59
ΔResidual Rate$_{k,t}$(bps)	-1	27	-127	-18	-4	12	128
MBS Yield$_t$(%)	2.99	0.41	2.18	2.69	2.94	3.39	3.88
ΔMBS Yield$_t$(bps)	-2	28	-47	-23	-8	19	76
Number of Licensed Appraisers$_{k,t}$	91	160	2	14	36	96	1846
Refinance-Per-Appraiser$_{k,t}$	2.1	1.8	0.2	0.8	1.5	2.8	12.6
Top 4 Lender Share$_{k,t}$(%)	38.9	12.3	13.3	30.1	37.4	45.6	87.6
Fintech Share$_{k,t}$(%)	6.2	3.7	0.2	3.3	5.8	8.6	33.2
House Price$_{k,t}$(thousands)	180.7	97.7	42.5	120.6	159.2	216.8	1318.1
Wage$_{k,t}$(thousands)	43.7	9.9	25.1	37.2	42.2	48.1	163.9
Homeownership Rate$_{k,t}$(%)	67.1	8.1	22.6	62.1	68.0	72.8	85.7
Population$_{k,t}$(millions)	0.4	0.7	0.0	0.1	0.2	0.4	10.1
Black Share$_{k,t}$(%)	12.0	12.7	0.4	2.4	7.5	17.2	73.5
Younger Than 19 Share$_{k,t}$(%)	25.5	3.0	16.4	23.9	25.4	27.0	39.5
Older Than 65 Share$_{k,t}$(%)	15.7	3.9	6.4	13.1	15.3	17.8	36.2
Bachelor Degree Share$_{k,t}$(%)	25.3	9.2	7.2	18.7	24.0	30.3	59.3

This table shows the summary statistics for the sample used in the robustness panel regression $\Delta\text{Residual Rate}_{k,t} = \beta_1\Delta\text{MBS Yield}_t + \beta_2\Delta\text{MBS Yield}_t \times \text{Refinance-Per-Appraiser}_{k,t} + \Gamma X_{k,t}+\alpha_k+\zeta_t+\varepsilon_{k,t}$. The sample uses quarterly data from 2012 to 2019, including 12,117 data points, covering 391 counties and 31 quarters. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Rate$_{k,t}$ is the average residual mortgage rate of county k and quarter t, after purging the impact of FICOs and LTVs for each loan. MBS yields are the current coupon rates of 30-year Fannie Mae MBS from Bloomberg. Refinance-Per-Appraiser$_{k,t}$ is the number of refinance loan originations acquired by Fannie Mae in county k and quarter t divided by the number of licensed appraisers in county k and the previous year of t, calculated using Fannie Mae's Loan Performance Dataset and the appraiser data from the National Registry of Appraisers. Top 4 Lender Share$_{k,t}$ is the total market share of the top 4 lenders ordered by origination volume, based on HMDA data. Fintech Share$_{k,t}$ is the market share of fintech lenders, based on HMDA data and fintech lender classifications in Fuster et al. (2018)Fuster, Plosser, Schnabl, and Vickery (2018). House Prices$_{k,t}$ is the value of a typical home provided by the Zillow Home Value Index. Wage$_{k,t}$ is the average wage of all industries from the BLS QCEW data. The last ten rows report summary statistics obtained from the U.S. Census data for the following control variables: homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher.

Table 1.6: Mortgage Rate Pass-through and Refinance-Per-Appraiser

Dependent Variable:	ΔResidual Rate$_t$				
Model:	(1)	(2)	(3)	(4)	(5)
ΔMBS Yield$_t$	0.692***	5.65**	3.82*	6.15**	3.33*
	(0.129)	(2.07)	(1.87)	(2.31)	(1.72)
Refinance-Per-Appraiser$_t$	-0.030***	-0.033***	-0.033***	-0.018***	-0.020***
	(0.005)	(0.005)	(0.006)	(0.003)	(0.005)
ΔMBS Yield$_t$ $\times$ Refinance-Per-Appraiser$_t$	-0.023*	-0.033**	-0.037**	-0.032**	-0.034*
	(0.011)	(0.012)	(0.012)	(0.013)	(0.018)
year	Yes	Yes		Yes	
county	Yes	Yes	Yes		
controls		Yes	Yes	Yes	Yes
Observations	3,375	3,375	3,375	3,375	3,375
R^2	0.82372	0.83916	0.81084	0.82305	0.78480
Within R^2	0.58847	0.62452	0.80983	0.58743	

Clustered (county & year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta\text{Residual Rate}_{k,t} = \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Refinance-Per-Appraiser}_{k,t} + \Gamma X_{k,t} + \nu_k + \xi_t + \varepsilon_{k,t}$$

Using quarterly data from 2012 to 2019, this table runs the above regression to investigate the relation between lender capacity pressures and mortgage rate pass-through, where refinance-per-appraiser is a proxy for capacity pressures. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Rate$_{k,t}$ is the average residual mortgage rate of county k and quarter t, after purging the impact of FICOs and LTVs for each loan. MBS yields are the current coupon rates of 30-year Fannie Mae MBS from Bloomberg. Refinance-Per-Appraiser$_{k,t}$ is the number of refinance loan originations acquired by Fannie Mae in county k and quarter t divided by the number of licensed appraisers in county k and the previous year of t, calculated using Fannie Mae's Loan Performance Dataset and the appraiser data from the National Registry of Appraisers. $X_{k,t}$ includes the following control variables: local market concentration measured by the total market share of top 4 lenders, fintech lender market shares, house prices, wages, homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher. ν_k is the county fixed effect and ξ_t is the year fixed effect. Standard errors are clustered by county and year. The third row shows the impact of lender capacity pressures on mortgage rate pass-through.

Table 1.7: Effective Date of Adopting Remote Online Notarization

State	RON Adoption Date
VA	2012-07-01
NV	2018-07-01
TX	2018-07-01
MI	2018-10-01
MN	2019-01-01
IN	2019-07-01
TN	2019-07-01
ND	2019-08-01
OH	2019-10-01
MT	2019-10-01
UT	2019-11-01
FL	2020-01-01
ID	2020-01-01
KY	2020-01-01
OK	2020-01-01
WI	2020-05-01
IA	2020-07-01
NE	2020-07-01
MO	2020-09-01
MD	2020-10-01
WA	2020-10-01
PA	2020-11-01
CO	2021-01-01
AK	2021-01-01
HI	2021-01-01

This table shows the legal adoption dates of remote online notarization (RON) for states which have passed RON laws as of 2021Q1. The data comes from DocuSign's website, which provides information for the history and current status of RON laws in each juridical state. For example, `https://www.docusign.com/products/notary/legality/alaska` gives the information for Alaska.

Table 1.8: Summary Statistics (Diff-in-Diff Regression)

	Mean	SD	Min	Q25	Q50	Q75	Max
Residual Spread$_{k,t}$(bps)	140	25	39	124	139	157	264
Top 4 Lender Share$_{k,t}$(%)	38.2	14.1	13.3	27.7	34.7	46.3	100.0
Fintech Share$_{k,t}$(%)	9.6	3.9	1.9	7.0	9.0	11.4	42.8
House Price$_{k,t}$(thousands)	233.8	176.5	46.2	136.6	187.2	269.3	2010.6
Wage$_{k,t}$(thousands)	48.5	13.4	27.4	40.0	45.8	53.3	205.9
Homeownership Rate$_{k,t}$(%)	66.6	9.0	19.0	61.4	67.5	72.7	90.2
Population$_{k,t}$(millions)	0.4	0.7	0.0	0.0	0.2	0.4	10.1
Black Share$_{k,t}$(%)	12.3	12.9	0.6	2.5	7.5	17.8	74.1
Younger Than 19 Share$_{k,t}$(%)	25.0	3.4	7.6	23.3	24.9	26.7	38.6
Older Than 65 Share$_{k,t}$(%)	17.4	5.0	7.3	14.2	16.6	19.4	59.1
Bachelor Degree Share$_{k,t}$(%)	24.9	9.6	6.0	18.0	23.5	30.6	59.2

This table shows the summary statistics for the sample (2016 to 2021) used in the diff-in-diff regression Residual Spread$_{k,t} = \sum_{i=-36}^{36} \beta_i \times \text{Treat}_{k,t,i} + \Gamma X_{k,t} + \nu_k + \zeta_t + \varepsilon_{k,t}$. The sample includes 31,465 data points, covering 565 counties and 63 months. 313 counties are in states with RON laws passed at some point during the sample period, and 252 counties are in states that had never authorized RON during the sample period. RON treatment data is derived from the history information of RON laws in each juridical state provided by DocuSign's website. Loan-level data for mortgage rates, loan and borrower characteristics are from Fannie Mae's Loan Performance Dataset. Residual Spread$_{k,t}$ is the gap between average residual rate in county k and month t over MBS yield in month t, where MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. Top 4 Lender Share$_{k,t}$ is the total market share of the top 4 lenders in origination volume, based on HMDA data. Fintech Share$_{k,t}$ is the market share of fintech lenders, based on HMDA data and fintech lender classifications in Fuster, Plosser, Schnabl, and Vickery (2018). House Prices$_{k,t}$ is the value of a typical home provided by the Zillow Home Value Index. Wage$_{k,t}$ is the average wage of all industries from the BLS QCEW data. The last six rows show summary statistics obtained from the U.S. Census data for the following control variables: homeownership rates, total population, population shares of black people, population shares of people younger than 19, population shares of people older than 65, and population shares of people with a Bachelor's degree or higher.

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CHAPTER 2

Mortgage Rate Pass-Through and Labor Market Frictions

2.1 Introduction

Between 2008 and 2014, the Federal Reserve executed three rounds of large-scale asset purchase program (Quantitative Easing) to put downward pressure on long-term interest rates, support mortgage markets, and improve financial market conditions[1]. While one of the major goals with this large-scale asset purchase program is to lower mortgage rates and support the housing market, researchers have documented inefficiencies in the pass-through from MBS yields to mortgage rates and the negative impact caused by operational capacity pressures of mortgage lenders, who serve as an intermediary between capital market investors and mortgage borrowers in the primary mortgage market. For example, Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013) document originator profits and unmeasured costs increased from less than 200 bps in 2008 to more than 500 bps in 2012. Sharpe and Sherlund (2016) find binding mortgage processing capacity constraints reduce purchase mortgage originations to borrowers of low to modest credit quality. Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021) show pandemic-related labor market frictions and operational bottlenecks caused higher intermediation markups set by mortgage lenders. In Chapter 1 of this dissertation, I also provide empirical evidence for the significant negative impact of

[1]In the first round, the Federal Reserve purchased $175 billion agency debt, $1.25 trillion agency MBS, and $300 billion long-term Treasury securities; in the second round, the Fed purchased $600 billion long-term Treasury securities; in the third round, the Federal Reserve purchased $790 billion Treasury securities and $823 billlion agency MBS. `https://www.newyorkfed.org/markets/programs-archive/large-scale-asset-purchases`

lender capacity pressures on mortgage rate pass-through in the recent decade.

The contribution of Chapter 2 is to enhance our understanding of mortgage rate pass-through in the primary market by highlighting the role of labor market frictions in causing lender operational capacity pressures. Though there exist papers providing empirical evidence for the impact of lender capacity pressures (Sharpe and Sherlund (2016), Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021), Choi, Choi, and Kim (2022)), this paper is the first to model how lender capacity pressures arise. First, I summarize stylized facts of mortgage rate pass-through observed in the primary market; Second, I present a search model involving both the mortgage market and the labor market to explain how labor market frictions lead to lender capacity pressures, and how these pressures dampen the pass-through from MBS yields to mortgage rates.

I begin to document two properties of mortgage rate pass-through observed in the primary mortgage market: imperfectness and rate dependency. As in Scharfstein and Sunderam (2015), I measure mortgage rate pass-through as the sensitivity of changes in mortgage rates to changes in MBS yields. Using quarterly data of mortgage rates from Freddie Mac's Primary Mortgage Market Survey and the current coupon rates for Fannie Mae 30-year MBS from Bloomberg, I find as MBS yields change by 100 bps, mortgage rates only change by 85 bps on average over the sample period from 2012 to 2019. Moreover, I find the pass-through worsens as interest rates decrease. Data shows when MBS yields are above its median level by one standard deviation, a 100 bps change in MBS yields leads to a 96 bps change in mortgage rates. But when MBS yields are below the median level by one standard deviation, mortgage rates only change by 68 bps.

Inspired by the empirical evidence in Chapter 1 about the negative impact of lender operational capacity pressures on mortgage rate pass-through, I build a model with searches happening in both the mortgage market and the labor market to investigate the cause for lender capacity pressures, which explains the imperfectness and rate dependency of mortgage rate pass-through. I leverage the Diamond-Mortensen-Pissarides (DMP) search framework (Diamond (1982), Mortensen (1982), Pissarides (2024)) to model the search and matching between borrowers and lenders in the mortgage market, as well as the search and matching between workers and lenders in the labor market. The interactions between the mortgage market and the labor market bring an interesting channel for labor market frictions to affect mortgage rate pass-through.

Starting from the mortgage market, I assume borrowers and lenders match according to a Cobb-Douglas matching function, which depends on the ratio of lender capacity over mortgage demand (mortgage market tightness). Both borrowers and lenders pay search costs to find a match and do Nash bargaining to split surplus when they match. Borrowers freely enter until their search costs adjusted by matching probabilities are equal to the benefit obtained from a loan. Mortgage demand and the average benefit from a loan is assumed to be negatively correlated. For example, as borrowers lower their refinance incentive thresholds, more seek to refinance. Therefore, the borrower entry condition determines mortgage demand; the Nash bargaining determines the relationship between mortgage rate and market tightness; and market tightness connects mortgage demand with lender capacity, where lender capacity is determined by the search in the labor market.

In the labor market, lenders and workers also match according to a Cobb-Douglas matching function, which depends on the ratio of job vacancies over the number of job seekers (labor market tightness). Both lenders and workers pay search costs to find a match and do Nash bargaining to split surplus when they match. Lenders freely enter to create job vacancies until their search costs adjusted by matching probabilities are equal to the benefit of hiring an additional worker. In the steady-state, the inflow to unemployment due to new separations from the previous employed offset the outflow from unemployment due to new hires from the previous unemployed. The benefit of hiring an additional worker depends on worker productivity, which is determined by mortgage rate and matching probabilities in the mortgage market.

The mortgage market and labor market are closely linked in the model. In one direction, the labor market search determines lender capacity in the mortgage market by affecting the number of workers employed; in the other direction, the mortgage market determines the equilibrium employment level in the labor market by affecting worker productivity. These interactions lead to interesting implications about the impact of lender capacity pressures on mortgage rate pass-through. When MBS yield decreases, mortgage rate decreases and mortgage demand increases. If lenders do not increase processing capacity, mortgage market tightness would decrease and mortgage spread would increase. If lenders do increase capacity, holding worker efficiency constant, they have to hire more workers; to hire more workers, they have to post more job vacancies to increase labor market tightness; to incentivize lenders to post more job vacancies, worker productivity has to increase; to increase worker productivity, mortgage market tightness has to decrease to increase matching probabilities for lenders, as well as mortgage spread in the mortgage market. Hence, as MBS yield decreases, due to labor market frictions, mortgage spread has to increase, resulting in a partial pass-through from MBS yields to mortgage rates. The model also explains the rate dependency of mortgage rate pass-through. Because of the congestion of matching in the labor market, labor market frictions are greater when labor market tightness is higher. Therefore, as interest rates decrease, mortgage demand increases, labor market tightness rises, frictions in capacity adjustment intensify, and mortgage rate pass-through worsens.

I calibrate the model using quarterly data from 2012 to 2019, allowing borrower bargaining power, worker bargaining power, and prepayment expectations to change over time to match the data moments. To highlight the key role of labor market frictions, I also run a forward prediction exercise, by using the calibrated parameters at the beginning of the sample and predict outputs for the rest sample period. The forward prediction does not match actual data as closely as the base model, but it generates similar dynamics featuring an imperfect mortgage rate pass-through that worsens as interest rates decrease. By holding all the parameters constant, the forward prediction identifies the impact from the channel of labor market frictions only. For example, the prediction shows even if borrower bargaining power does not change, the model still explains most of the behaviors of mortgage rate pass-through in the recent decade, verifying the important role of labor market frictions.

Lastly, I run three counterfactuals and explore ways to improve mortgage rate pass-through: increasing total labor supply in the mortgage industry, increasing worker efficiency, and reducing labor market search costs. The result shows both increasing labor supply and increasing worker efficiency significantly lower mortgage spread, while reducing labor market search costs has a negligible impact. The economic impact of either increasing labor supply or worker efficiency by 20% on a 30 year mortgage loan with a balance of 200K and a starting mortgage rate of 4% is about 16 bps on mortgage rate, $28 on monthly payment, and $46-48K on future value. In contrast, the economic impact of reducing labor market search costs by 20% is only 0.5 bps on mortgage rate. The first two strategies are much more effective than the third one because labor supply and worker efficiency directly affect lender capacity, while search costs only indirectly affect lender capacity through changing labor market tightness.

Another important implication from the counterfactual analysis is that a one-time positive shock to labor supply or worker efficiency only lowers mortgage spread once and does not improve mortgage rate pass-through in the future. To achieve an effective mortgage rate pass-through, the market needs to be elastic in a way that either labor supply or worker efficiency could be adjusted upward swiftly whenever interest rates decrease, enabling the mortgage industry to accommodate surging mortgage demand.

Literature and contribution. As mentioned in Chapter 1, this paper contributes to the literature examining the pass-through from monetary policies to homeowners' borrowing costs (Hancock and Passmore (2011), Stroebel and Taylor (2012), Di Maggio, Kermani, and Palmer (2020)), the literature investigating intermediation roles of mortgage lenders in the transmission of monetary policies (Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013), Scharfstein and Sunderam (2015), Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013)), and the literature of price dispersion and search frictions in the mortgage market (Alexandrov and Koulayev (2017), Bhutta, Fuster, and Hizmo (2020), Gurun, Matvos, and Seru (2016), Ambokar and Samaee (2019), Agarwal, Grigsby, Hortaçsu, Matvos, Seru, and Yao (2020)).

To my knowledge, this paper is the first to present a structural model to explain capacity pressures of mortgage lenders and why these pressures affect mortgage rate pass-through. Several papers study the impact of lender capacity constraints in the mortgage market but none of them present a model to explain the cause of capacity constraints or the mechanism of how these constraints affect mortgage rate pass-through. Papers providing empirical evidence include Fuster, Goodman, Lucca, Madar, Molloy, and Willen (2013), Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021), Choi, Choi, and Kim (2022), as well as Chapter 1 in this dissertation. Sharpe and Sherlund (2016) present a structural model to explain the credit rationing impact of lender capacity constraints but do not speak to mortgage rate pass-through. In contrast, my paper presents a search model to discover the channel of labor market frictions in causing lender capacity pressures, which in turn leads lenders to charge higher markups in the mortgage market as an incentive to hire and expand capacity.

Lastly, this paper contributes to the search literature studying interactions between different markets. Petrosky-Nadeau and Wasmer (2015) build a model with search frictions in goods, labor, and credit markets, and find goods market frictions are key in generating persistence in labor market dynamics. Gabrovski and Ortego-Marti (2021) develop a model with search frictions in both the financial sector and the housing market to measure the impact of credit market shocks to housing prices, time-to-sell, and mortgage debt-to-price ratio. My paper presents a model with search happening in both the mortgage market and the labor market to study why mortgage lenders could not scale up processing capacity freely without charging higher markups in the mortgage market.

The rest of the paper proceeds as follows. Section 2 summarizes properties of mortgage rate pass-through in the primary market. Section 3 outlines the search model explaining lender operational capacity pressures and the impact on mortgage rate pass-through. Section 4 describes the model calibration and performance. Section 5 presents counterfactual analysis. Section 6 concludes.

2.2 Stylized Facts

In this section, I present two stylized facts of mortgage rate pass-through in the primary mortgage market. First, the sensitivity of changes in mortgage rates to changes in MBS yields is less than 1, which I describe as a property of 'imperfectness'. Second, this sensitivity decreases as the level of interest rates decreases, which I refer to as 'rate dependency'.

2.2.1 Imperfectness

The goal of the Federal Reserve's program to purchase mortgage-backed securities is 'to provide support to mortgage and housing markets and to foster improved conditions in financial markets more generally'[2]. Ideally, the decrease in MBS yields caused by this large purchase should be passed 100% to mortgage rates. However, data from 2012 to 2019 shows this pass-through is only 85% on average, which means 15% of the policy subsidy is captured by mortgage lenders, either to improve profits or to cover increased costs.

The first chart in Figure 2.1 plots quarterly changes of mortgage rate against changes of MBS yield. Data for average mortgage rate is from Freddie Mac's Primary Mortgage Market Survey, which gathers inputs from lenders on their first-line prime conventional confirming 30-year fixed rate home purchase mortgages with a loan-to-value of 80%. Data for MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. The slope of the linear fitted line measures the sensitivity of mortgage rate changes to MBS yield changes and shows 85% of MBS yield changes passed through to mortgage rate. Hence, the pass-through from MBS yield to mortgage rate is imperfect.

The second chart in Figure 2.1 plots primary mortgage spread (the difference between mortgage rate and MBS yield) against MBS yield, which shows mortgage spread is increasing as MBS yield decreases. This negative correlation between mortgage spread and MBS yield is a natural outcome of the imperfect mortgage rate pass-through: when MBS yield decreases, mortgage rate decreases by a smaller amount, enlarging mortgage spread. This points out a fallacy of using mortgage spread to measure mortgage rate pass-through. Even when the sensitivity of mortgage rate to MBS yield stays constant, mortgage spread could increase as interest rate decreases, as long as the pass-through is less than 100%. Hence, I use the sensitivity of mortgage rate changes to MBS yield changes to measure mortgage rate pass-through.

[2] `https://www.newyorkfed.org/markets/mbs_faq.html`

2.2.2 Rate Dependency

Dividing the sample data into periods with different levels of interest rates, I find the magnitude of mortgage rate pass-through also varies significantly with interest rates. Figure 2.2 plots the same chart as Figure 2.1 but splits the sample points into two sub-samples based on the level of MBS yield: red points are for periods when MBS yield is above its median and blue points are for periods when MBS yield is below its median. The figure shows when MBS yield is higher than its median (2.9%), the sensitivity of mortgage rate changes to MBS yield changes is 0.96. But when MBS yield is lower than its median, the sensitivity of mortgage rate changes to MBS yield changes is only 0.68. This means the pass-through from MBS yield to mortgage rate decreases by 28% from a high rate environment to a low rate environment.

Formally, Table 2.1 runs a regression to illustrate this rate-dependent behavior of mortgage rate pass-through:

$$\Delta\text{Mortgage Rate}_t = \beta_0 + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative MBS Yield}_t + \varepsilon_t$$

where $\Delta\text{Mortgage Rate}_t$ is the quarterly change of mortgage rate, $\Delta\text{MBS Yield}_t$ is the quarterly change of MBS yield, and $\text{Relative MBS Yield}_t$ is the difference between MBS yield at quarter t and the median MBS yield over the sample period. I use relative MBS yield in the regression so the estimated coefficient β_1 can be interpreted as the pass-through when MBS yield is at its median level. As shown in Table 2.1, mortgage rate pass-through is 0.788 when MBS yield is at its median, confirming the imperfectness of mortgage rate pass-through. Also, mortgage rate pass-through weakens significantly as interest rates decrease: when MBS yield decreases from one standard deviation (41 bps) above its median to one standard deviation below its median, the pass-through decreases from 0.93 to 0.64[3].

To increase monetary policy effectiveness and household welfare, it is important to understand what hinders mortgage rate pass-through in the primary mortgage market. Moreover,

[3] $0.788 - 41/100 * 0.347 = 0.64, 0.788 + 41/100 * 0.347 = 0.93$

a weakening pass-through as interest rates decrease is particularly concerning because it reduces the impact of interest rate cuts during economic downturns when households are most needy. In Chapter 1, I provide empirical evidence for the negative impact of lender operational capacity pressures on mortgage rate pass-through. This channel of capacity pressures is also consistent with the observed worsening of mortgage rate pass-through as interest rates decrease. As shown in Figure 2.3, when interest rates decrease, mortgage demand increases (the first panel); when mortgage demand increases, days-to-close increases (the second panel). Therefore, when interest rates are lower, lender capacity pressures are stronger, leading to a weaker mortgage rate pass-through.

In this paper, I argue capacity pressures are indeed critical in causing mortgage rate pass-through to be imperfect and rate dependent. In the next section, I present a search model with searches happening in both the mortgage market and the labor market to explain the mechanism of how lender capacity pressures arise and how they affect mortgage rate pass-through.

2.3 Model

I leverage the Diamond-Mortensen-Pissarides (DMP) search framework to model how borrowers and lenders meet in the mortgage market to determine mortgage rate, as well as how lenders and mortgage industry workers meet in the labor market to determine employment. The interactions between searches happening in these two markets provide insights into causes for lender capacity pressures and the associated impact on mortgage rate pass-through.

2.3.1 Search in the Mortgage Market

I begin to introduce the search process in the mortgage market. Assume time is continuous and there is a representative lender in the mortgage market whose loan processing capacity is K. Meanwhile, the number of mortgage applications from borrowers is A. The aggregate number of matches between the lender and borrowers is

$$M(K, A) = \tau K^{1-\gamma} A^{\gamma}, \gamma \in (0, 1) \tag{M}$$

This matching function is commonly assumed in the search literature and satisfies the following assumptions: (i) $M(K, A)$ is increasing in (K, A); (ii) $M(K, A)$ is constant returns to scale; (iii) $M(K, A)$ is concave in (K, A). The first assumption says the number of matches is increasing in the number of participants; the second assumption suggests when the market doubles in size, the number of matches also doubles in size; the third assumption implies the matching process is subject to congestion as the number of participants increases.

Mortgage market tightness is defined as the ratio of lender capacity over the number of mortgage applications

$$\phi = \frac{K}{A} \tag{ϕ}$$

The mortgage market is described as 'tight' (or 'slack') when lender capacity is abundant (or scarce) relative to the number of mortgage applications.

The matching probability of a capacity unit is the number of total matches divided by the number of total capacity units, which is a decreasing function of market tightness

$$\frac{M(K, A)}{K} = \tau \phi^{-\gamma} = p(\phi) \tag{p}$$

That is, when the market is tight with abundant lender capacity relative to mortgage demand, the matching probability for a capacity unit is lower and it takes longer for the lender to find matched borrowers.

The matching probability of a mortgage application is the number of total matches divided by the number of total mortgage applications, which is an increasing function of market tightness

$$\frac{M(K, A)}{A} = \tau \phi^{1-\gamma} = g(\phi) \tag{g}$$

That is, when the market is tight with abundant lender capacity relative to mortgage demand, it takes less time for a borrower to find a matched lending opportunity.

In the steady-state, we have the following four Bellman equations

$$rK_0 = -c^K + p(\phi)(K_1 - K_0) \tag{K_0}$$

$$K_1 = \lambda(m - y) - \zeta \tag{K_1}$$

$$rA_0 = -c^A + g(\phi)(A_1 - A_0) \tag{A_0}$$

$$A_1 = \rho(\mu(A) - m) - \delta \tag{A_1}$$

where K_0 is the value function of an unmatched capacity unit, K_1 is the value function of a matched capacity unit, A_0 is the value function of an unmatched mortgage application, A_1 is the value function of a matched mortgage application, r is discount rate, m is primary mortgage rate, and y is secondary mortgage rate (MBS yield).

Equation (K_0) says the flow value of an unmatched capacity unit is a positive net gain of $K_1 - K_0$ if getting matched minus the lender's search cost for borrowers c^K, where the probability of match for a capacity unit is $p(\phi)$.

Equation (K_1) says the value of a matched capacity unit is the revenue of loan origination $\lambda(m-y)$ minus the origination cost ζ, where λ is a lender revenue multiplier that depends on the prepayment speeds of borrowers. For a typical originate-to-distribute lender, choosing a higher mortgage rate means the lender could sell the loan into an MBS with a higher coupon. So the revenue from increasing mortgage rate depends on the slope of MBS prices against coupon rates. As interest rates get lower, refinance increases more for MBS bonds with higher coupons, leading to a flatter MBS price curve against coupon rates. Therefore, I expect λ to be positively correlated with y[4], which will be used as a testing condition for the calibrated model.

Equation (A_0) says the flow value of an unmatched mortgage application is a positive net gain of $A_1 - A_0$ if getting matched minus the search cost of borrowers for a lender c^A,

[4]Another intuitive way to understand this is as interest rates (y) decrease, borrowers prepay faster and lenders earn the mortgage spread ($m - y$) for a shorter period of time, meaning λ is smaller.

where the probability of match for a mortgage application is $g(\phi)$.

Equation (A_1) says the value function of a matched mortgage application is the benefit from obtaining the loan $\rho(\mu(A)-m)$, minus the origination fee δ. $\mu(A)$ denotes the borrower's utility each period from the loan. For a purchase loan, $\mu(A)$ could be a constant housing utility flow. Each period, the borrower enjoys the housing while paying the mortgage rate m. For a refinance loan, $\mu(A)$ is the original mortgage rate. By refinancing, the borrower pays off the old loan, equivalent to capturing the original mortgage rate each period, while paying the new mortgage rate m. I assume borrowers estimate their benefit of getting the loan as a constant ρ times the net utility each period $\mu(A) - m$. For example, ρ could be 75 if borrowers assume they hold the loan for 7 years (84 months) with an annual discount rate of 3.5%

$$\sum_{i=1}^{84} \frac{1}{(1+r)^i} = 75 \tag{2.1}$$

In Equation (A_1), I assume the borrower's utility $\mu(A)$ is a decreasing function of A. Because as more borrowers refinance, the average original mortgage rate is lower, meaning borrowers are willing to refinance at a smaller refinance incentive. For simplicity, assume $\mu(A) = a + blog(A), b < 0$.

When a match happens between the lender and a borrower, they bargain over mortgage rate and the trade surplus is split according to Nash bargaining

$$\frac{A_1 - A_0}{K_1 - K_0} = \frac{\alpha}{1-\alpha}$$

where $\alpha \in (0, 1)$ is the borrower's bargaining power.

Assuming free entry of borrowers, the value of an unmatched mortgage application A_0 is driven down to 0. Combined with the Bellman equations and Nash bargaining, the steady-state equilibrium in the mortgage market is summarized by the following claim

Claim 2.3.1. *The steady-state equilibrium in the mortgage market search is characterized* *by the following three questions:*

$$\frac{c^A}{g(\phi)} = \rho(\mu(A) - m) - \delta \tag{BE}$$

$$\frac{c^A(r + p(\phi))}{(r\lambda(m - y) - r\zeta + c^K)g(\phi)} = \frac{\alpha}{1 - \alpha} \tag{Pm}$$

$$\phi = \frac{K}{A} \tag{ϕ}$$

Equation (BE) is the borrower entry condition derived from $A_0 = 0$. Borrowers enter until the search cost adjusted by matching probabilities on the left side equals the benefit from the loan on the right side. Equation (Pm) is the mortgage rate pricing equation, derived from Nash bargaining and the Bellman equations (Appendix 2.7.1). Equation (ϕ) is the definition of market tightness. Note that lender capacity K is determined by the labor market since the lender has to hire workers in the labor market to process mortgage loans, which will be described in the next section.

2.3.2 Search in the Labor Market

In this section, I describe the search process in the labor market for the mortgage industry. Suppose the lender posts V job vacancies. The total labor supply in the mortgage industry is T, among which U are unemployed and $T - U$ are employed. Employed workers separate randomly from the lender at rate s. The aggregate number of matches between job vacancies and unemployed workers is

$$H(V, U) = \chi V^{1-\eta} U^{\eta}, \eta \in (0, 1) \tag{H}$$

which takes the same form as the matching function in the mortgage market and satisfies the usual assumptions of matching functions in the search literature: (i) increasing in (V, U); (ii) constant returns to scale; (iii) concave in (V, U).

Labor market tightness is defined as the ratio of job vacancies over the unemployment level

$$\theta = \frac{V}{U} \tag{θ}$$

The labor market is 'tight' ('slack') when job openings are abundant (scarce) relative to the unemployed.

The matching probability of a job vacancy is the number of hires divided by the number of job vacancies, which is a decreasing function of market tightness

$$\frac{H(V,U)}{V} = \chi\theta^{-\eta} = q(\theta) \tag{q}$$

That is, when the market is tight with abundant job vacancies relative to the unemployed, it takes longer for a job vacancy to get filled.

The matching probability of a job seeker is the number of hires divided by the number of unemployed, which is an increasing function of market tightness

$$\frac{H(V,U)}{U} = \chi\theta^{1-\eta} = f(\theta) \tag{f}$$

That is, when the market is tight with abundant job vacancies relative to the unemployed, it takes less time for a job seeker to find a matched position.

In the steady-state, we have the following four Bellman equations

$$rV_0 = -c^V + q(\theta)(V_1 - V_0) \tag{V_0}$$

$$rV_1 = x - w + s(V_0 - V_1) \tag{V_1}$$

$$rU_0 = -c^U + f(\theta)(U_1 - U_0) \tag{U_0}$$

$$rU_1 = w + s(U_0 - U_1) \tag{U_1}$$

where V_0 is the value function for an unmatched job vacancy, V_1 is the value function for a matched job vacancy, U_0 is the value function for an unmatched job seeker, and U_1 is the value function for a matched job seeker.

Equation (V_0) says the flow value of an unmatched job vacancy is a positive net gain of

$V_1 - V_0$ if getting matched minus the lender's search cost for workers c^V, where the probability of match for a job vacancy is $q(\theta)$.

Equation (V_1) says the flow value of a matched position is worker productivity x deducted by wage w and a loss of $V_1 - V_0$ if the worker separates, which happens at rate s.

Equation (U_0) says the flow value of job searching is a positive net gain of $U_1 - U_0$ if getting matched minus the worker's search cost for employers c^U, where the probability of match for a job seeker is $f(\theta)$.

Equation (U_1) says the flow value of a hired worker is wage w minus a loss of $U_1 - U_0$ if being separated, which happens at rate s.

The law of motion for unemployment in the labor market is

$$\frac{dU}{dt} = (T - U)s - Uf(\theta)$$

That is, the change in unemployment comes from two flows: the inflow due to new separations from the previous employed and the outflow due to new hires from the previous unemployed.

When a match happens between a lender and a worker, they bargain over wage and the trade surplus is split according to Nash bargaining

$$\frac{U_1 - U_0}{V_1 - V_0} = \frac{\beta}{1 - \beta}$$

where $\beta \in (0, 1)$ is the worker's bargaining power.

Assuming free entry of job vacancies in the labor market, the value of an unmatched job vacancy V_0 is driven down to 0. Combined with the Bellman equations, Nash bargaining, and the law of motion for unemployment, the steady-state equilibrium in the labor market is summarized by the following claim

Claim 2.3.2. *The steady-state equilibrium in the labor market search is characterized by the* *following three equations:*

$$U = \frac{Ts}{s + f(\theta)} \tag{U}$$

$$\frac{c^V}{q(\theta)} = \frac{x - w}{r + s} \tag{VE}$$

$$w = \beta(x + \theta c^V) - (1 - \beta)c^U \tag{P_w}$$

Equation (U) determines the steady-state unemployment level, derived from setting $dU/dt = 0$. Equation (VE) is the vacancy entry condition, derived from $V_0 = 0$. Lenders keep posting new job vacancies until the search cost adjusted by matching probabilities on the left side equals the benefit of hiring an additional worker on the right side. Equation (P_w) is the wage pricing equation, derived from Nash bargaining and the Bellman equations (Appendix 2.7.2). Note that worker productivity x is determined by the mortgage market, which will be described in the next section.

2.3.3 Links Between the Two Markets

To close this model, I now specify the links between the two markets: in Claim 2.3.1, labor capacity K is determined by the labor market equilibrium; in Claim 2.3.2, worker productivity x is determined by the mortgage market equilibrium.

In detail, the labor market determines lender capacity in the mortgage market by

$$K = e(T - U) \tag{K}$$

where e is worker efficiency, defined as the number of loans one worker could process within a unit of time. The equation says lender capacity is the level of employment multiplied by worker efficiency.

Meanwhile, market tightness and pricing in the mortgage market determine worker productivity in the labor market

$$\begin{aligned} x &= \frac{M(K,A)}{T-U}(\lambda(m-y)-\zeta) \\ &= \frac{M(K,A)}{K}\frac{K}{T-U}(\lambda(m-y)-\zeta) \\ &= p(\phi)(\lambda(m-y)-\zeta)e \end{aligned} \tag{x}$$

where $\lambda(m-y)-\zeta$ is the net profit of originating one loan, and $M(K,A)/(T-U)$ is the number of loans originated by one worker. The multiplication of the two is the productivity of one worker, which is determined by the matching probability of lending in the mortgage market $p(\phi)$, mortgage spread $m-y$, and worker efficiency e.

2.3.4 Equilibrium

Given Claim (2.3.1)(2.3.2) and Equations $(K)(x)$, the equilibrium with searches happening in the mortgage market and the labor market is summarized in the following definition.

Definition 1. ***Equilibrium***

Given the following:

(i) mortgage market parameters: borrower search cost c^A, lender search cost c^K, matching parameters $\{\tau,\gamma\}$, borrower bargaining power α, borrower utility parameters $\{a,b\}$, loan origination fee δ, loan origination cost ζ, borrower revenue multiplier ρ, lender revenue multiplier λ;

(ii) labor market parameters: worker search cost c^U, lender search cost c^V, matching parameters $\{\chi,\eta\}$, worker bargaining power β, worker efficiency e, worker separation rate s;

(iii) discount rate r;

(iv) exogenous processes of MBS yield y and labor supply T;

*The **equilibrium** consists of 8 endogenous variables:*

mortgage rate m, mortgage market tightness ϕ, lender capacity K, mortgage demand A, labor market wage w, labor market tightness θ, worker productivity x, the level of unemployment U

such that *the following 8 equations are satisfied:*

$$
\begin{array}{lll}
(P_m) & \dfrac{c^A(r+p(\phi))}{(r\lambda(m-y)-r\zeta+c^K)g(\phi)} = \dfrac{\alpha}{1-\alpha} & \textit{mortgage rate pricing} \\
\textit{(BE)} & \dfrac{c^A}{g(\phi)} = \rho(\mu(A)-m) & \textit{borrower free entry} \\
(\phi) & \phi = \dfrac{K}{A} & \textit{mortgage market tightness} \\
\textit{(VE)} & \dfrac{c^V}{q(\theta)} = \dfrac{x-w}{r+s} & \textit{job vacancy free entry} \\
(P_w) & w = \beta(x+\theta c^V)-(1-\beta)c^U & \textit{wage pricing} \\
(U) & U = \dfrac{Ts}{s+f(\theta)} & \textit{unemployment} \\
(K) & K = e(T-U) & \textit{lender capacity} \\
(x) & x = p(\phi)(\lambda(m-y)-\zeta)e & \textit{worker productivity}
\end{array}
$$

Given the equilibrium, I derive the following proposition, which explains how labor market frictions lead to lender capacity pressures (decreasing mortgage market tightness) when interest rate decreases and how this results in an imperfect mortgage rate pass-through (increasing mortgage rate spread).

Proposition 1. *Holding all else constant, when MBS yield y decreases, the equilibrium mortgage market tightness ϕ decreases and mortgage spread $m-y$ increases.*

Proof. When MBS yield y decreases, suppose mortgage spread $m-y$ does not increase, I will show this leads to a contradiction, thus proving mortgage spread $m-y$ does increase.

When y decreases, suppose mortgage spread $m-y$ decreases (or stays constant), to make Equation (Pm) hold, mortgage market tightness ϕ must increase (or stays constant). Given a lower mortgage rate m and a higher (or unchanged) mortgage market tightness ϕ, the borrower's free entry condition (BE) implies borrower utility $\mu(A)$ must decrease. Hence, more borrowers enter and A increases ($\mu'(A) < 0$). To increase (or maintain) ϕ, lender capacity K must increase. From Equation (K), unemployment must decrease. From Equation (U), labor market tightness θ must increase. Then from Equation (VE)(P_w), worker productivity x must increase. But this contradicts with Equation (x), which says worker productivity x cannot be higher since ϕ increases (or stays constant) and $m-y$ decreases (or stays constant).

Hence, when MBS yield y decreases, mortgage spread $m - y$ increases, and mortgage market tightness ϕ decreases. This is consistent with the empirical evidence that when interest rate decreases, lenders face more capacity pressures (smaller mortgage market tightness ϕ), and mortgage spread increases, implying an imperfect pass-through from MBS yields to mortgage rates. □

Labor market frictions play a key role here in impeding mortgage rate pass-through. Given the search and matching in the mortgage market, to keep mortgage spread constant when interest rate decreases, mortgage market tightness ϕ must also stay constant (Equation (Pm)), which means lenders have to expand capacity as rate decreases and mortgage demand increases. However, due to labor market frictions, lenders have to increase labor market tightness to hire more workers, which has to be incentivized by higher worker productivity. To provide such incentives, lenders have to charge a higher markup in the mortgage market by raising mortgage spread and increase lending matching probabilities by lowering mortgage market tightness (Equation (x)).

The model also explains why mortgage rate pass-through gets worse when interest rate decreases, as shown in the following corollary.

Corollary 1. *Holding all else constant,* $\dfrac{dm}{dy}$ *is smaller when* y *is lower.*

From Proposition 1, when MBS yield y decreases, the lender has to increase labor market tightness θ to decrease unemployment U and increase employment $T - U$. Because of the congestion of matching in the labor market, $H(U, V)$ is concave in U and V. Then $f(\theta) = H(U, V)/U = H(1, \theta)$ is concave in θ. Given the steady-state unemployment $U = \dfrac{Ts}{s + f(\theta)}$ and a target amount of change in U, the concavity of $f(\theta)$ indicates a bigger change in θ is required when θ is higher. When interest rate is lower and mortgage demand is higher, labor market for the mortgage industry is tighter. In such a low rate environment with a high θ, when negative rate shocks hit, it requires a bigger increase in θ to expand capacity due to the congestion in matching, which in turn requires a bigger increase in worker productivity as an incentive. This incentive has to be provided by the mortgage market in the form of a lower market tightness (higher matching probability for the lender) and higher mortgage spread, thus leading to a smaller mortgage rate pass-through.

2.3.5 Removing Labor Market Frictions

To demonstrate the key role of labor market frictions, consider the case when lenders can freely expand capacity in the mortgage market so the value of an unmatched lending capacity unit K_0 is driven down to 0. The steady-state equilibrium in the mortgage market search is then summarized in the following claim.

Claim 2.3.3. *If lenders can freely enter, the steady-state equilibrium in the mortgage market search is characterized by the following four equations:*

$$\frac{c^K}{p(\phi)} = \lambda(m - y) - \zeta$$
$$\frac{c^A}{g(\phi)} = \rho(\mu(A) - m)$$
$$\frac{c^A}{c^K \phi} = \frac{\alpha}{1 - \alpha}$$
$$\phi = \frac{K}{A}$$

The first equation comes from the lender free entry condition; the second equation comes from the borrower free entry condition; the third equation comes from Nash bargaining; and the last equation defines the mortgage market tightness. Holding all parameters constant, the third equation implies a constant market tightness ϕ, no matter how MBS yield y changes. Then the first equation implies a constant mortgage spread $m - y$. The second equation implies mortgage demand A increases and the last equation implies lender capacity K rises to keep market tightness ϕ constant. Therefore, if lenders can freely expand capacity, both mortgage market tightness and mortgage spread remain constant, which is inconsistent with the empirical observation of increasing lender capacity pressures and higher mortgage spread when interest rates decrease and mortgage demand surges.

To sum up, I have presented a model with searches happening in both the mortgage market and the labor market to explain the key role of labor market frictions in causing lender operational capacity pressures, which in turn cause mortgage rate pass-through to be imperfect (Section 2.2.1) and rate dependent (Section 2.2.2).

2.4 Calibration

2.4.1 Calibration Procedure

I calibrate the model to satisfy the steady-state equilibrium equations in Definition 1 using quarterly data from 2012 to 2019.

For the mortgage market, mortgage rate m is the 30-year mortgage rate from Freddie Mac's Primary Mortgage Market Survey (PMMS), which gathers inputs from lenders on their first-line prime conventional confirming 30-year fixed rate home purchase mortgages with a loan-to-value of 80%; secondary mortgage rate y is MBS yield, approximated by the current coupon rate of 30-year Fannie Mae MBS from Bloomberg; mortgage applications A and originations M are from the Mortgage Market Activity and Trends Reports published by the Consumer Financial Protection Bureau (CFPB)[5]; lender origination cost per loan (including personnel cost) is obtained from the Mortgage Bankers Quarterly Performance Reports published by the Mortgage Bankers Association[6].

For the labor market, employment $T-U$ is the employment level of the real estate credit industry from the BLS QCEW program; real wage w is the wage level of the real estate credit industry from the same dataset deflated by the inflation index from the CRSP; labor supply T is approximated by $T = (T-U)/(1-u)$, where u is the unemployment rate of the real estate industry from the BLS Current Population Survey (CPS); unemployment U is the difference between labor supply T and employment $T-U$; job vacancy is approximated

[5] https://www.consumerfinance.gov/data-research/research-reports/data-point-2019-mortgage-market-activity-and-trends/

[6] https://www.mba.org/news-and-research/research-and-economics/single-family-research/mortgage-bankers-performance-reports-quarterly-and-annual

by $V = (T - U)/(1 - o)o$, where o is the job opening rate of the real estate industry from the BLS Job Openings and Labor Turnover Survey (JOLTS). New hire is approximated by $H = (T - U)h$, where h is the hiring rate of the real estate industry from JOLTS;[7] [8]

Given the above data sources, I calibrate the model parameters using the following procedure, which is also summarized in Table 2.2.

Discounting. Discount rate r is set to be 0.0086 so the annual rate is 3.5%. The borrower revenue multiplier ρ is set to be $\sum_{i=1}^{7\times 4} \frac{1}{(1+r)^i} = 25$[9], assuming borrowers consider enjoying the benefit from the loan for 7 years.

Search costs. In the mortgage market, borrower search cost c^A is set to be 29.7 bps, which is the estimated average search cost for an additional lender inquiry in Agarwal, Grigsby, Hortaçsu, Matvos, Seru, and Yao (2020); lender search cost c^K is set to be 10 bps arbitrarily. In the labor market, lender search cost c^V is set to be 157 bps, which is 14% of the mean wage over the sample period, as estimated in Silva and Toledo (2009); worker search cost c^U is set to be 0, assuming the unemployment benefit is offset by the search cost. The values of these parameters do not affect the main result of this paper.

Worker efficiency. Worker efficiency e is defined as the maximum number of mortgage loans each worker could process within a quarter. I approximate worker efficiency by the maximum originations-per-worker over the sample period. Figure 2.4 plots originations-per-worker over the history: during periods with low demand, originations-per-worker was low and workers might not run at their full capacity; during periods with high demand, such as the refinance wave after the financial crisis at the end of 2012, originations-per-worker reached its peak and workers were likely to run at their full capacity. I set worker efficiency as 12, which is the peak number at the end of 2012. This approach does not consider time varying factors that could affect worker efficiency. For example, if regulation becomes more

[7] To adjust for seasonality, I use the 4-quarter moving average for unemployment rate, job opening rate, and hiring rate.

[8] In JOLTS, hiring is a flow variable for the past month, while opening is a state variable on the last day of a month. To make $H \leq \min\{V, U\}$, I adjust the hiring rate by multiplying 70%.

[9] Using quarterly data, $\rho = 25$. If using monthly data, $\rho = 75$, as described in Section 2.3.1.

stringent and efficiency decreases, this approach would overestimate worker efficiency in the more recent sample.

Separation rate. From the data of hires and unemployment, I calculate the matching probability of a worker $f(\theta) = H/U$. Combined with the data of labor supply, the steady-state unemployment can be calculated using Equation (U) for any given value of the separation rate s. I calibrate separation rate $s = 0.02$ such that the average model output of unemployment matches the average unemployment in the actual data.

Borrower origination fee. For borrowers, I assume they pay an origination fee $\delta = 500$ bps of the loan amount. That is, they pay an origination cost of 1K for a mortgage loan with a balance of 200K.

Lender origination cost. Lender origination cost ζ is calculated as the average $C - w/e$ over the sample period (221 bps), where C is average total origination cost per loan (including personnel cost) of mortgage lenders and w/e is wage per loan given worker efficiency e.

Borrower utility. I assume borrower utility is a linear function of mortgage demand: $\mu(A) = a + blog(A)$. This reduced form tracks the relationship that mortgage demand is higher when borrowers require a smaller utility ($b < 0$). Given the data of mortgage rates, originations, applications, origination fee, borrower revenue multiplier, and search costs, I calculate $\mu(A)$ using the borrower entry condition (BE). A linear regression of $\mu(A)$ against $log(A)$ shows that as mortgage demand increases by 10%, borrower utility per period decreases by 13 bps, which is significant at 1% level and the regression has an adjusted R-squared of 0.55.

Matching in the mortgage market. From the data of employment and worker efficiency, I calculate lender capacity $K = e(T - U)$. Combined with the data of mortgage applications, I calculate the number of matches M using the matching function (M) for any given value of the matching parameters $\{\tau, \gamma\}$. I calibrate $\{\tau = 0.63, \gamma = 1\}$ such that the model output of M matches the actual data of mortgage originations in terms of the first and second moments. Though the best fit shows lender capacity K does not affect the number of mortgage originations ($\gamma = 1$), it still affects mortgage market tightness and mortgage rates.

Matching in the labor market. From the data of job vacancies and unemployment, I calculate the number of matches in the labor market using the matching function (H) for any given value of the matching parameters $\{\chi, \eta\}$. I calibrate $\{\chi = 0.64, \eta = 0.34\}$ such that the model output of H matches the actual data of hires in terms of the first and second moments. The elasticity of matching to the number of job seekers is 0.34 and the elasticity of matching to the number of job vacancies is 0.66.

Bargaining powers and lender revenue multiplier. For each quarter, given a set of values for borrower bargaining power α, worker bargaining power β, and lender revenue multiplier λ, I solve the equilibrium using Definition 1. I calibrate the parameters quarter by quarter to match the actual data of mortgage rate m, wage w, and labor market tightness θ.

2.4.2 Performance

Given the calibrated parameters in Table 2.2, the data for labor supply T and MBS yield y, I solve for the equilibrium for each quarter from 2012Q1 to 2019Q4. To assess the model performance, I plot the actual data and model outputs in Figure 2.6 for the mortgage market and Figure 2.7 for the labor market.

In Figure 2.6, mortgage spread $m-y$, number of mortgage applications A, lender capacity K, mortgage market tightness ϕ, mortgage originations M, and matching probability of lender capacity $p(\phi)$ are plotted, with the actual data in blue lines and the model output in red lines. The figure shows the model matches the actual data closely, especially for mortgage spread in the first figure which is one of the target in the quarter-by-quarter calibration. The second panel shows the number of mortgage applications is volatile, which also drives the volatile mortgage originations in the fifth panel. Given the volatile mortgage applications in the second panel and the persistent lender capacity in the third panel, mortgage market tightness in the fourth panel ends up to be volatile. Mortgage market tightness in the fourth panel is negatively correlated with the matching probability of lending in the last panel.

In Figure 2.7, wage w, unemployment level U, job vacancies V, labor market tightness θ, hires H, and matching probability of a job vacancy $q(\theta)$ for the mortgage industry are plotted. The model matches the actual data closely, especially for wage in the first panel and labor market tightness in the fourth panel, which are among the targets for the quarter-by-quarter calibration. The second panel shows a declining trend of unemployment in the recent decade. Meanwhile, job vacancies in the third panel and labor market tightness in the fourth panel show an increasing trend. New hires in the fifth panel has the same cyclical patterns as job vacancies in the third panel. Matching probability of job vacancy in the last panel is negatively correlated to labor market tightness in the fourth panel.

The close match between the model output and the actual data provides evidence for the model's validity. Note that the match for mortgage market tightness serves as a testing moment which is not among the target moments for calibration.

More evidence supporting the model can be found by comparing the model calibrated lender revenue multiplier with the survey data from the Mortgage Bankers Association. I gather the quarterly Mortgage Bankers Performance Reports, which include survey data of mortgage lenders' average revenue per loan originated. Dividing revenue per loan by mortgage spread, I calculate a survey-implied lender revenue multiplier. Figure 2.8 shows the model calibrated and survey implied lender revenue multiplier closely track each other and have a high correlation of 0.81. Given that the survey data does not use any model assumptions and is not used in the model calibration, the close match between the model calibrated and survey implied data provides strong evidence for the model's validity. Furthermore, the second panel in Figure 2.8 shows lender revenue multiplier (both the model calibrated value and the survey-implied value) is positively correlated with MBS yield, which is consistent with our expectation described in Section 2.3.1.

2.4.3 Time-varying Parameters

The model allows three parameters to change over time, including borrower bargaining power α, worker bargaining power β, and lender revenue multiplier λ. Figure 2.5 plots the calibrated parameters, where the left column shows the time series and the right column plots the parameters against MBS yield y.

The first row in Figure 2.5 shows the calibrated borrower bargaining power is decreasing with MBS yield. This is counter-intuitive if we think borrowers bargaining power is lower when interest rates decrease and mortgage demand increases. However, this emphasizes the importance of labor market frictions in generating the dynamics of imperfect mortgage rate pass-through. When interest rates decrease, even if borrower bargaining power increases, the model still generates higher mortgage spread, due to labor market frictions. The second row shows the calibrated worker bargaining power has been decreasing in the recent decade, consistent with the finding in Stansbury and Summers (2020). The scatter-plot shows a weak negative correlation between the calibrated worker bargaining power and MBS yield, which contributes partially to higher mortgage spreads as interest rates decrease. The third row shows the calibrated lender revenue multiplier λ is increasing with MBS yield y, consistent with the survey data and the expectation of slower prepayment speeds as interest rates decrease. From Equation (x), this also contributes partially to the higher mortgage spread as MBS yield decreases.

One may wonder if the dynamics of mortgage rate pass-through observed in the data is caused by these time-varying parameters, or the time-varying labor supply T, instead of being generated by the channel of labor market frictions. To highlight the key role of labor market frictions, I run a forward prediction exercise by using the parameter values and labor supply T at the starting period 2012Q1, holding them constant, and generating predictions for the rest of the sample periods, given the actual path of MBS yield y. Since all the parameters and labor supply are held constant throughout the sample period, this exercise shows the impact of the channel of labor market frictions only.

Figure 2.9 shows all the main properties of mortgage rate pass-through still hold. The first panel shows the model predicted mortgage spread has similar dynamics as the actual data. Nevertheless, the model's prediction is more volatile than the actual data, since we shut down the variation of parameter values and labor supply. For example, labor supply may adjust accordingly with market demand in the real world, thus reducing the volatility of mortgage spread. The second panel plots mortgage spreads against MBS yields. Both the model prediction and the actual data show a negative correlation between mortgage spreads and MBS yields, consistent with an imperfect mortgage rate pass-through. The third panel plots the change in the predicted mortgage rates against the change in MBS yields, where the red points are for periods when MBS yields are above the median and the purple points are for periods when MBS yields are below the median. The slope of the red points is higher than that of the purple points by 0.23, consistent with the empirical finding that mortgage rate pass-through worsens when MBS yields are lower.

Formally, Table 2.3 runs the same regression as in Table 2.1 but uses the model predicted mortgage rate on the left-hand side instead of the actual mortgage rate. The coefficient in the fourth row measures the variation of mortgage rate pass-through with the level of interest rates. As shown in the table, the model predicted mortgage rate pass-through is increasing in MBS yield: as MBS yield increases from 50 bps below its median to 50 bps above its median, the predicted pass-through increases by 0.314 significantly, similar to the impact of 0.347 in Table 2.1 which uses the actual data.

The above results confirm the key role of labor market frictions in generating mortgage rate pass-throughs that are imperfect and varying with the level of interest rates. This exercise with constant parameters also provides an ideal laboratory to inspect the mechanism of labor market frictions as described in Proposition 1 and Corollary 1.

From Proposition 1, when MBS yield decreases, due to labor market frictions, lenders have to increase labor market tightness to hire more workers, which has to be incentivized by higher worker productivity. Worker productivity is driven by mortgage spread and matching probabilities in the mortgage market (Equation (x)), both of which are decreasing in market tightness (Equation (Pm)). Hence, to increase worker productivity, mortgage market tightness has to decrease. Figure 2.10 plots the model output variables to verify this mechanism, holding all parameters constant. As shown in the figure, as MBS yield decreases, labor market tightness increases (the first panel), employment increases (the second panel), worker productivity increases (the third panel), market tightness decreases (the fourth panel), and mortgage spread increases (the fifth panel). The negative correlation between mortgage spread and MBS yield in the fifth panel shows the mortgage rate pass-through is imperfect, as shown in the right panel of Figure 2.1. Because of labor market frictions, lenders cannot expand capacity unless being incentivized by higher worker productivity.

From Corollary 1, mortgage rate pass-through decreases as interest rate decreases because the labor market matching gets more congested when rates are lower and labor market is tighter. In that case, it requires a bigger increase in labor market tightness to expand capacity, which in turn requires a bigger change in mortgage market tightness and mortgage spread as an incentive. The increased labor market frictions result in a weaker mortgage rate pass-through. As shown in the last panel of Figure 2.10, employment is concave in labor market tightness. As labor market tightness gets higher, the curve is flatter, meaning a bigger increase in labor market tightness is required to induce the same amount of expansion in the worker force. This channel of labor market frictions explains why mortgage rate pass-through is smaller when interest rates are lower.

2.5 Counterfactuals

After understanding the impact of labor market frictions on mortgage rate pass-through, I run three counterfactuals to explore ways to reduce the negative impact of labor market frictions and improve mortgage rate pass-through: increasing labor supply by 20%, increasing worker efficiency by 20%, and reducing lender search cost for workers by 20%.

From Equations $(K)(U)$, we get

$$K = \frac{eTf(\theta)}{s + f(\theta)} \tag{K'}$$

This implies to achieve a given level of lender capacity K, either increasing labor supply or increasing worker efficiency reduces labor market tightness θ, which requires a smaller worker productivity x as an incentive (Equation VE). Then from Equation (x), mortgage market tightness increases and mortgage spread decreases, resulting in a bigger mortgage rate pass-through. A lower labor market tightness θ also reduces the congestion of matching in the labor market, mitigating frictions in labor adjustment. Therefore, I expect both strategies to enhance mortgage rate pass-through and abate its variation with the level of interest rates.

From Equation (VE), a reduction of c^V would increase labor market tightness θ, holding all else constant. Then from Equations (K'), a higher labor market tightness would increase lender capacity, thus increasing mortgage market tightness and reducing mortgage spread. A higher mortgage market tightness and a lower mortgage spread also decrease worker productivity x. An increase in θ and a decrease in x will happen simultaneously when c^V decreases to make Equation (VE) hold. Therefore, I also expect reducing lender search cost to enhance mortgage rate pass-through.

The result of these counterfactuals is shown in Figure 2.11, where the first panel plots the time series and the second panel plots the predicted mortgage spread against MBS yield. The first panel shows both increasing labor supply and increasing worker efficiency significantly lower mortgage spread, while reducing lender search cost has a negligible impact. This is verified in Table 2.5, which shows the economic impact of these counterfactuals on the average mortgage rate, monthly payment, and future value of a 30 year mortgage rate loan with a balance of 200K and a starting mortgage rate of 4% over the sample period from 2012Q1 to 2019Q4. Increasing either T or e by 20% lowers mortgage rate by about 16 bps, monthly mortgage payment by about \$28, and future value of the loan by \$46-48K. Reducing lender search cost by 20% only lowers mortgage rate by 0.5 bps, monthly payment by less than a dollar and future value by 1.5K.

The second panel in Figure 2.11 shows no noticeable difference between the slopes of mortgage spreads against MBS yield, which is verified in Table 2.4. The second row shows increasing T or e improves mortgage rate pass-through but the difference is economically insignificant. The fourth rows shows increasing T or e abates the variation of mortgage rate pass-through as interest rates change, but the impact is also economically insignificant. The result tells us that increasing T or e to a higher level as a one-time shock decreases mortgage spread significantly but does not improve mortgage rate pass-through going forward, as long as labor market frictions exist. Though higher levels of T or e shift the regime of mortgage spread downward, to improve mortgage rate pass-through, it is not the levels of T or e that matter, but the abilities to increase T or e timely when y decreases that matter.

To understand why the impact of decreasing lender search cost is so small as compared to the impact of increasing labor supply or worker efficiency. Table 2.6 summarizes the key output variables of the model. The row for θ shows as labor supply T increases, labor market tightness decreases from 1.038 to 0.555; as worker efficiency e increases, labor market tightness decreases to 0.655; but as lender search cost c^V decreases, labor market tightness increases from 1.038 to 1.288, which is due to a lower cost for lenders to post vacancies. The row for $T - U$ shows as T increases, employment increases from 221K to 260K; as e increases, employment decreases from 221K to 218K because fewer workers are needed given the higher worker efficiency; as c^V decreases, employment increases only slightly from 221K to 222K. The row for lender capacity shows as T increases, lender capacity increases from 2.67M to 3.14M; as e increases, lender capacity increases similarly to 3.15M; but as c^V decreases, lender capacity only increases slightly to 2.68M. Therefore, the table shows the impact of changing c^V on lender capacity is much smaller as compared to changing T or e. Intuitively, changing T or e affects lender capacity directly through Equation (K'), while changing c^V affects lender capacity indirectly by influencing labor market tightness. The increased θ also makes the congestion of matching in the labor market worse, thus not being helpful in improving mortgage rate pass-through.

The counterfactual analysis shows effective ways to reduce mortgage spread include increasing labor supply and increasing worker efficiency. To improve mortgage rate pass-through, the market needs to be elastic so that labor supply and worker efficiency could be adjusted upward fast when MBS yield decreases and mortgage demand surges. One limitation of the model is that it does not speak to how borrower bargaining power, worker bargaining power, or lender revenue multiplier changes, but simply calibrate these parameters quarter by quarter to match the actual data. Due to the close relationship between lender revenue multiplier and prepayment expectations, it is possible that changing T, e, or c^V would not change lender revenue multiplier, given the same path of MBS yield. However, borrower bargaining power and worker bargaining power could be endogenously affected by T, e, or c^V, which brings caveats to the counterfactual analysis.

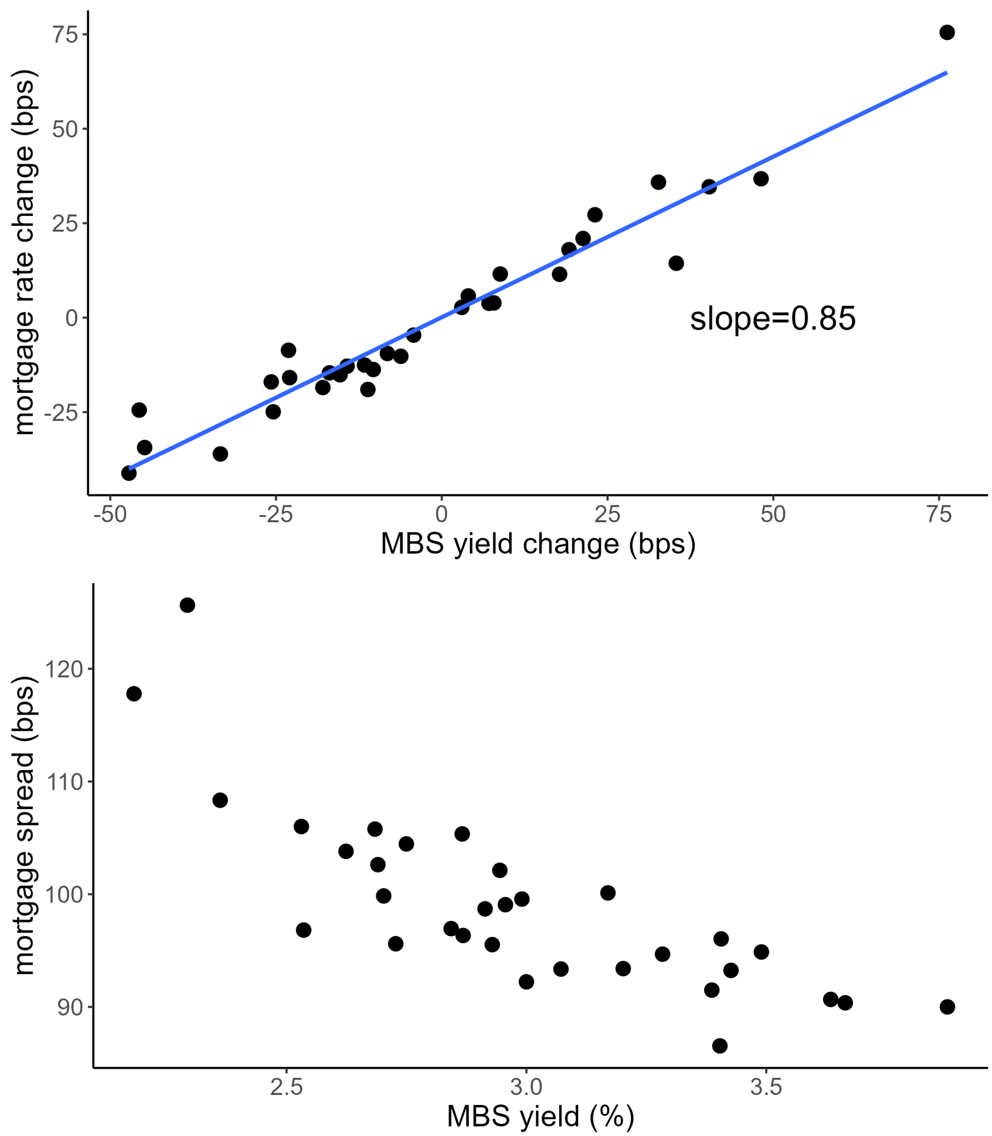
2.6 Conclusion

This chapter unravels mortgage rate pass-through in the primary mortgage market, where mortgage lenders play a key role as intermediaries between capital market investors and mortgage borrowers. Empirically, I document the imperfectness and rate dependency as important properties of mortgage rate pass-through. Theoretically, I find mortgage lenders face labor market frictions in expanding operational capacity, which leads to higher markups and lower matching probabilities for borrowers in the mortgage market. This channel of labor market frictions impedes mortgage rate pass-through more severely when interest rates are low, mortgage demand is high, and labor market is tight.

This chapter's finding has important implications for policy markers. First, policy makers have been focusing on improving mortgage market itself such as reducing market concentration to improve household welfare, but this chapter shows interactions between markets could bring new problems, such as lender capacity pressures caused by labor market frictions. Second, the counterfactual analysis implies an effective way to improve mortgage rate pass-through is to stay elastic in adjusting labor supply or worker efficiency. One solution is to invest in technology and digitalize the mortgage origination process, which makes lender operational capacity scalable and less dependent on the size of workforce. The support from policy makers could stimulate such technology advancement, for example, by encouraging electronic appraisal, authorizing online remote notarization, and accepting digital mortgage records by county offices.

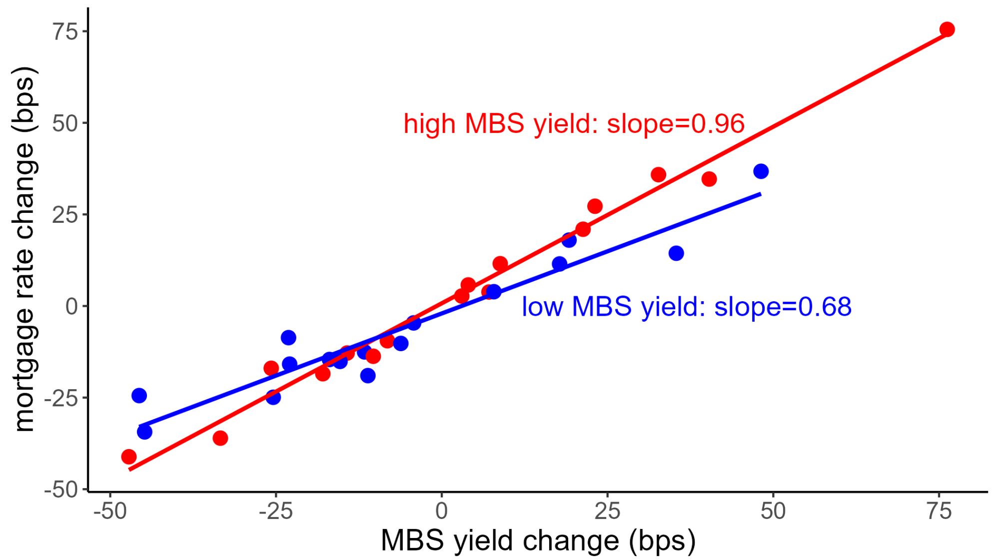
This chapter also has limitations. First, the model calibrates parameters quarter by quarter using steady-state equations without considering fluctuations away from the steady-state path, which could generate interesting dynamics. Second, the model assumes constant parameters in the matching functions in both the mortgage market and the labor market. An interesting future research project is to investigate whether changes in market conditions could change the matching functions.

Figure 2.1: Imperfect Mortgage Rate Pass-through



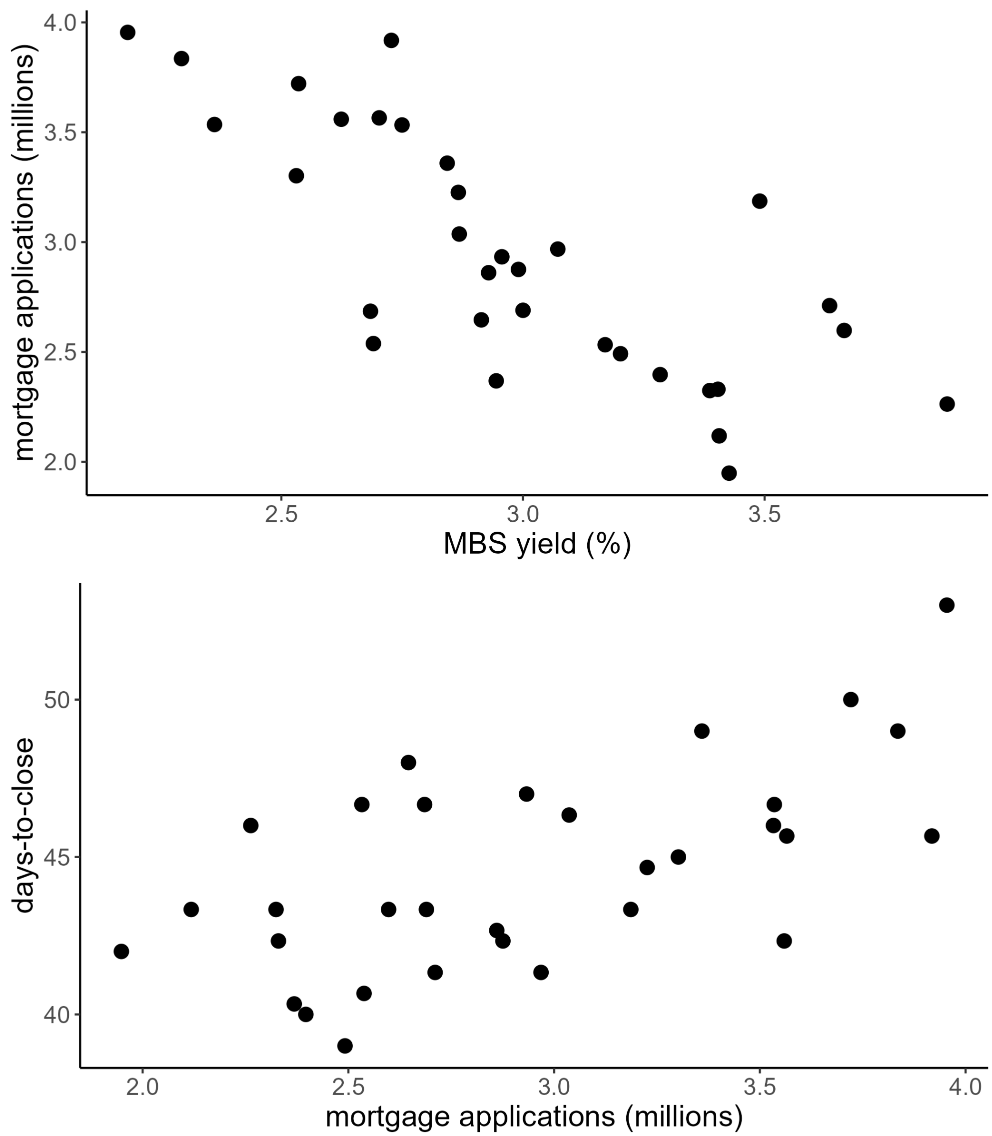
This figure demonstrates the imperfectness of mortgage rate pass-through, where the pass-through is measured by the sensitivity of changes in mortgage rate to changes in MBS yield. The first chart plots quarterly changes of mortgage rate against changes of MBS yield using data from 2012 to 2019. Data for mortgage rate is from Freddie Mac's Primary Mortgage Market Survey. Data for MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. The second chart plots primary mortgage spread (the difference between mortgage rate and MBS yield) against MBS yield.

Figure 2.2: Mortgage Rate Pass-through in Different Rate Environments



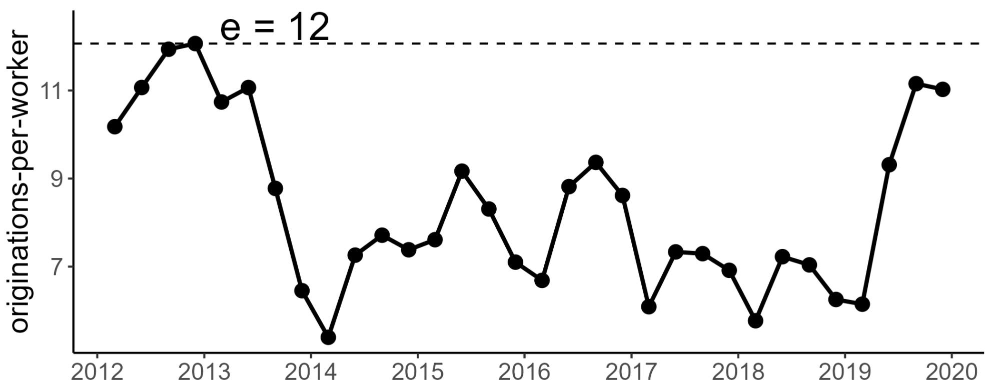
This figure plots mortgage rate changes against MBS yield changes, using quarterly data from 2012 to 2019. Data for mortgage rate is from Freddie Mac's Primary Mortgage Market Survey. Data for MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. The sample points are split into two sub-samples based on the level of MBS yield: red points are for periods when MBS yield is above its median over the sample period (2.9%) and blue points are for periods when MBS yield is below its median.

Figure 2.3: Interest Rate, Mortgage Demand, and Lender Capacity Pressures



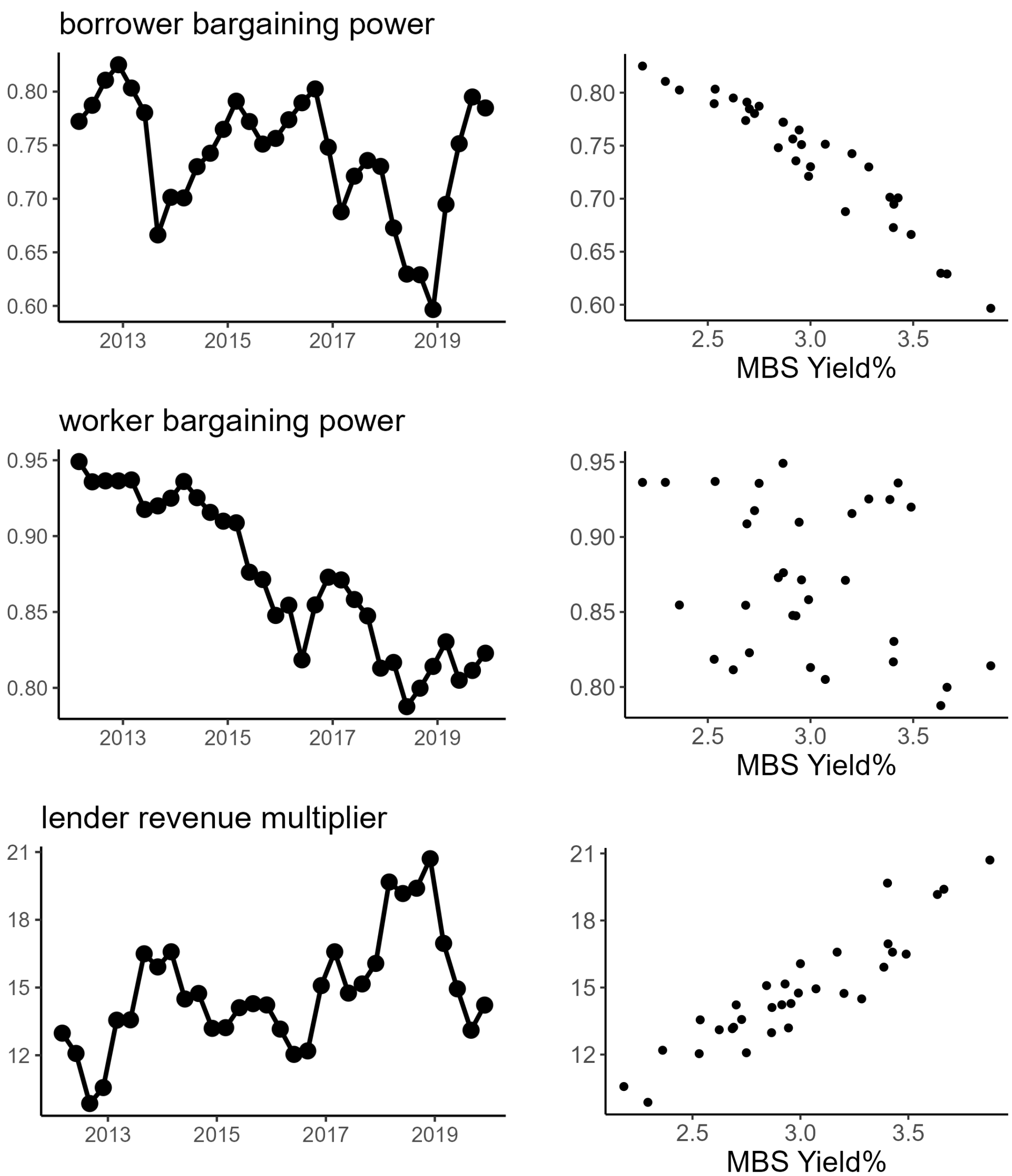
The first chart in this figure plots the number of mortgage applications against MBS yield over the period from 2012 to 2019. The second chart plots average days-to-close against the number of mortgage applications, where days-to-close is the number of days from mortgage application to closing. Data for mortgage applications is from HMDA. Data for MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg. Data for days-to-close is from Ellie Mae's Origination Insight Reports.

Figure 2.4: Worker Efficiency



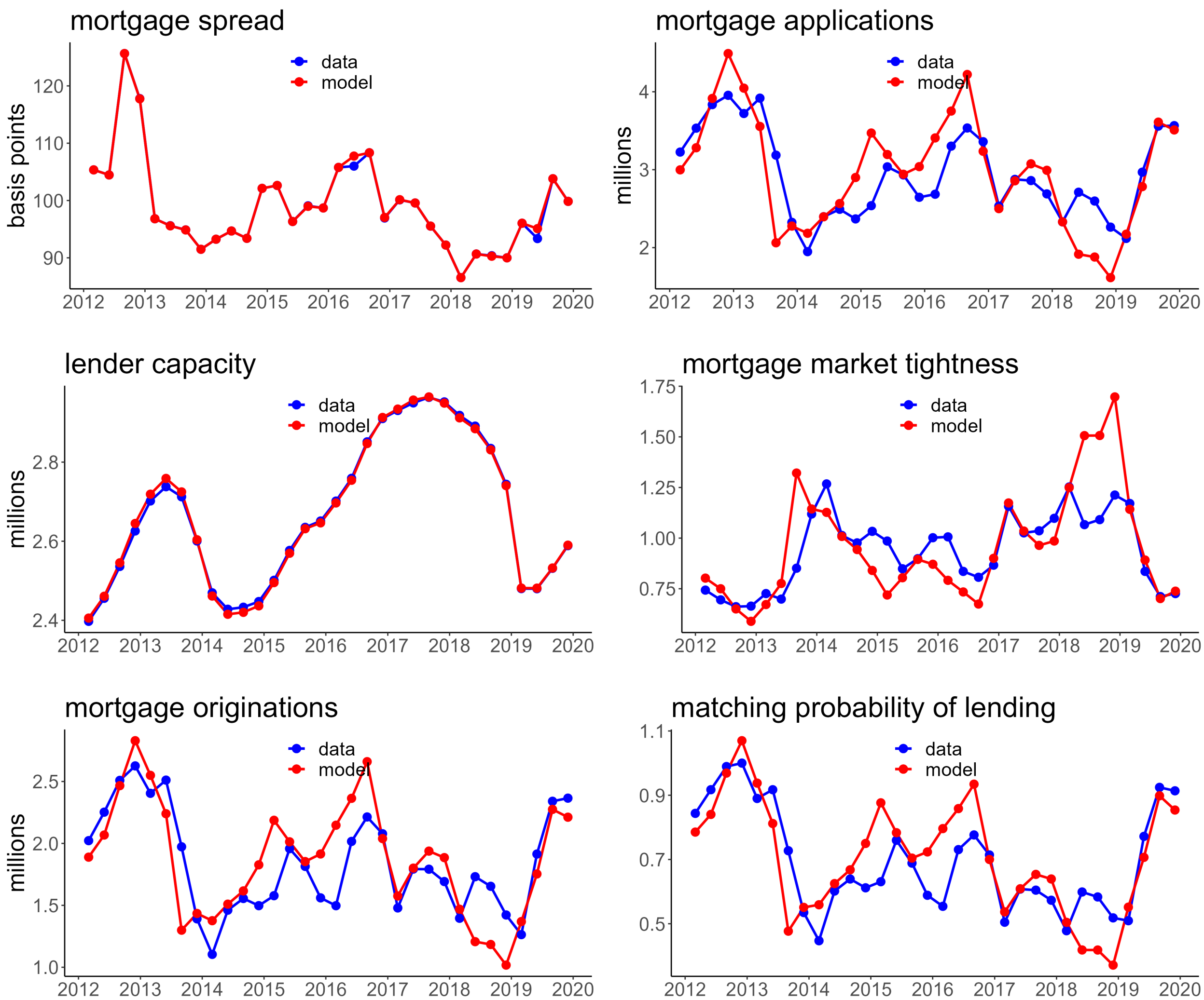
This figure plots the number of total mortgage originations over the number of workers employed in the mortgage industry from 2012 to 2019. The number of total mortgage originations is from HMDA. The number of workers employed in the mortgage industry is from the BLS QCEW program, filtering for the real estate credit industry and the private sector. Worker efficiency is set as the maximum of originations-per-worker over the sample period, which is 12 during the refinance wave after the financial crisis at the end of 2012.

Figure 2.5: Calibrated Time-Varying Parameters



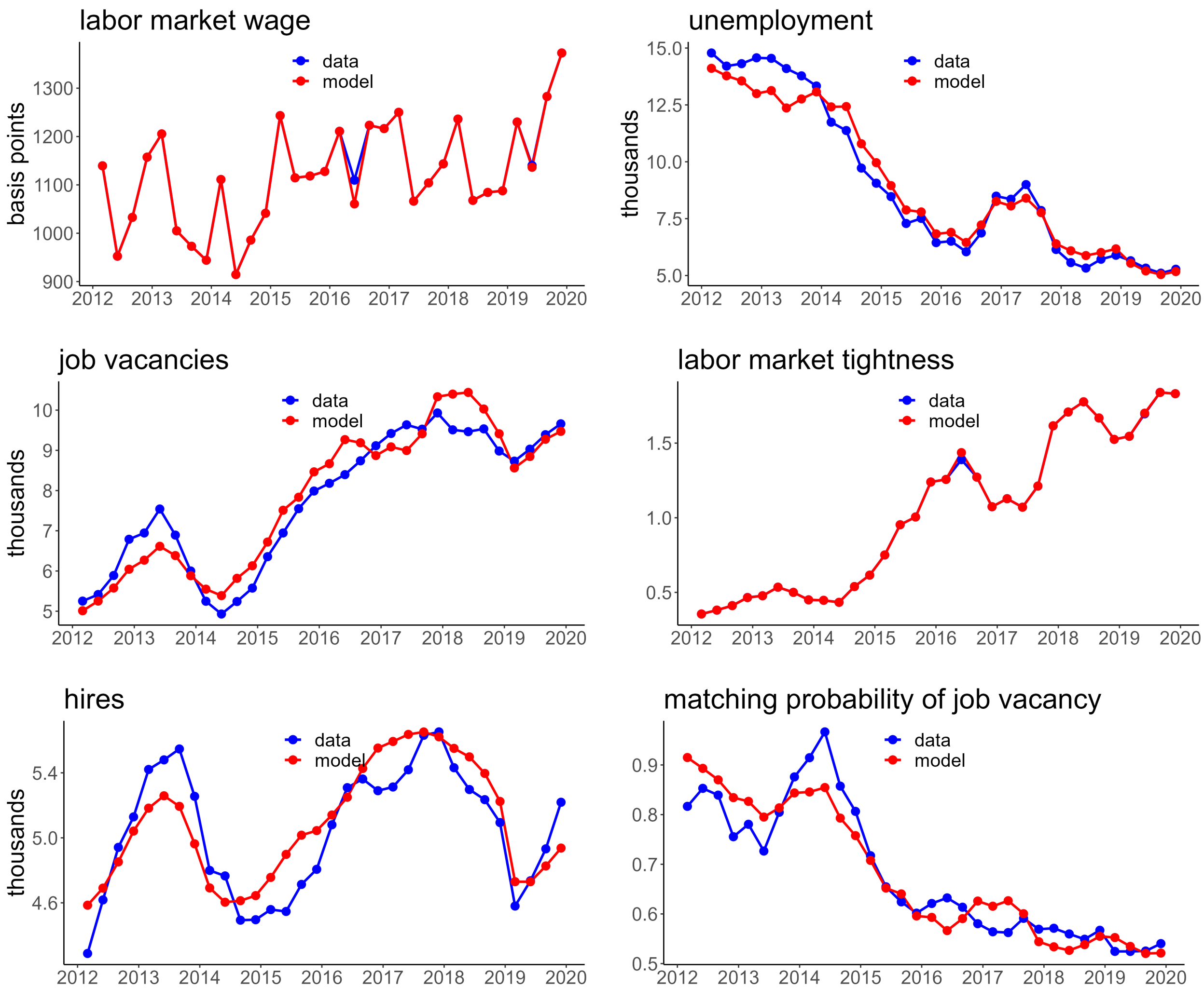
This figure plots the calibrated values of borrower bargaining power α, worker bargaining power β, and lender revenue multiplier λ. The calibration is done quarter by quarter to match the values of mortgage rate, wage, and labor market tightness at each quarter. The left column is the time series of calibrated parameter values and the right column is the scatter plots of parameter values against MBS yield.

Figure 2.6: Model vs. Data in the Mortgage Market



This figure plots the model output and actual data for the mortgage market, where the six panels are mortgage spread $m - y$, number of mortgage applications A, lender capacity K, mortgage market tightness θ, mortgage originations M, and matching probability of a lender capacity unit $q(\theta)$ respectively.

Figure 2.7: Model vs. Data in the Labor Market

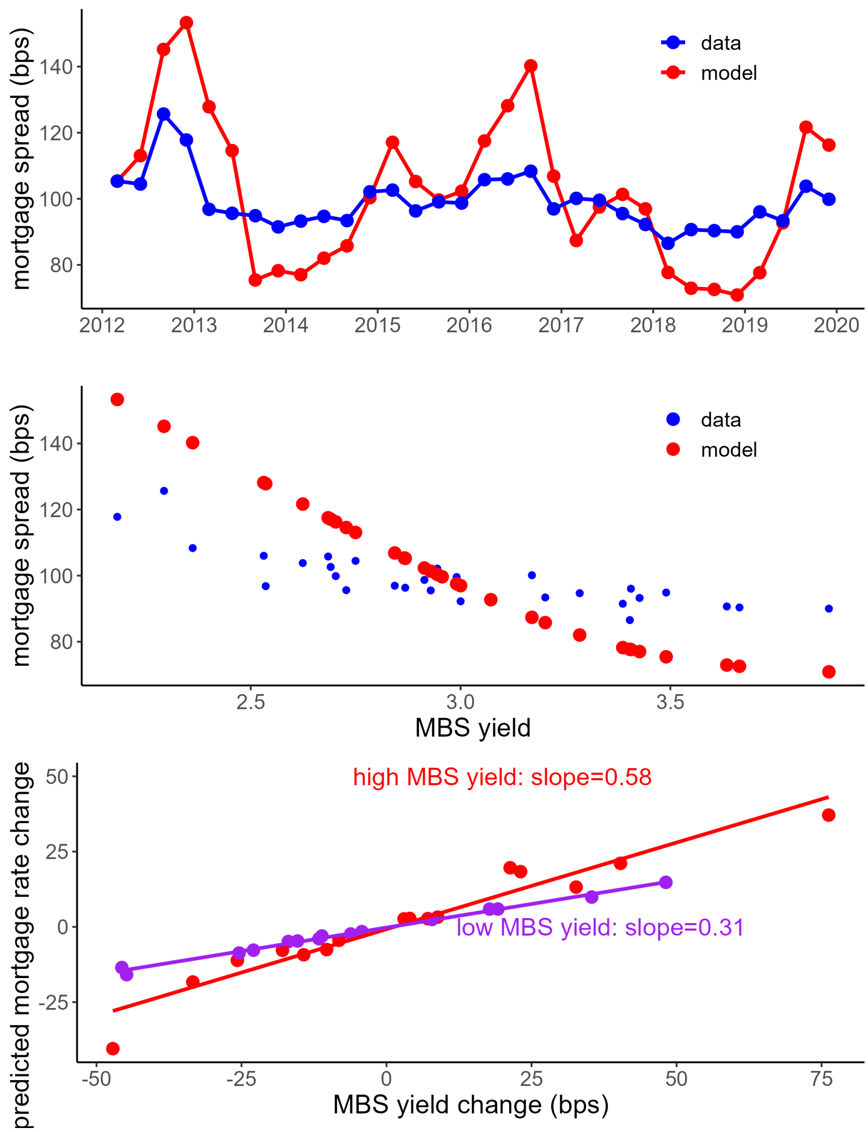


This figure plots the model output and actual data for the labor market, where the six panels plot wage w, unemployment level U, job vacancies V, labor market tightness ϕ, hires H, and matching probability of a job vacancy $p(\phi)$ for the mortgage industry respectively.

Figure 2.8: Lender Revenue Multiplier: Survey vs. Model

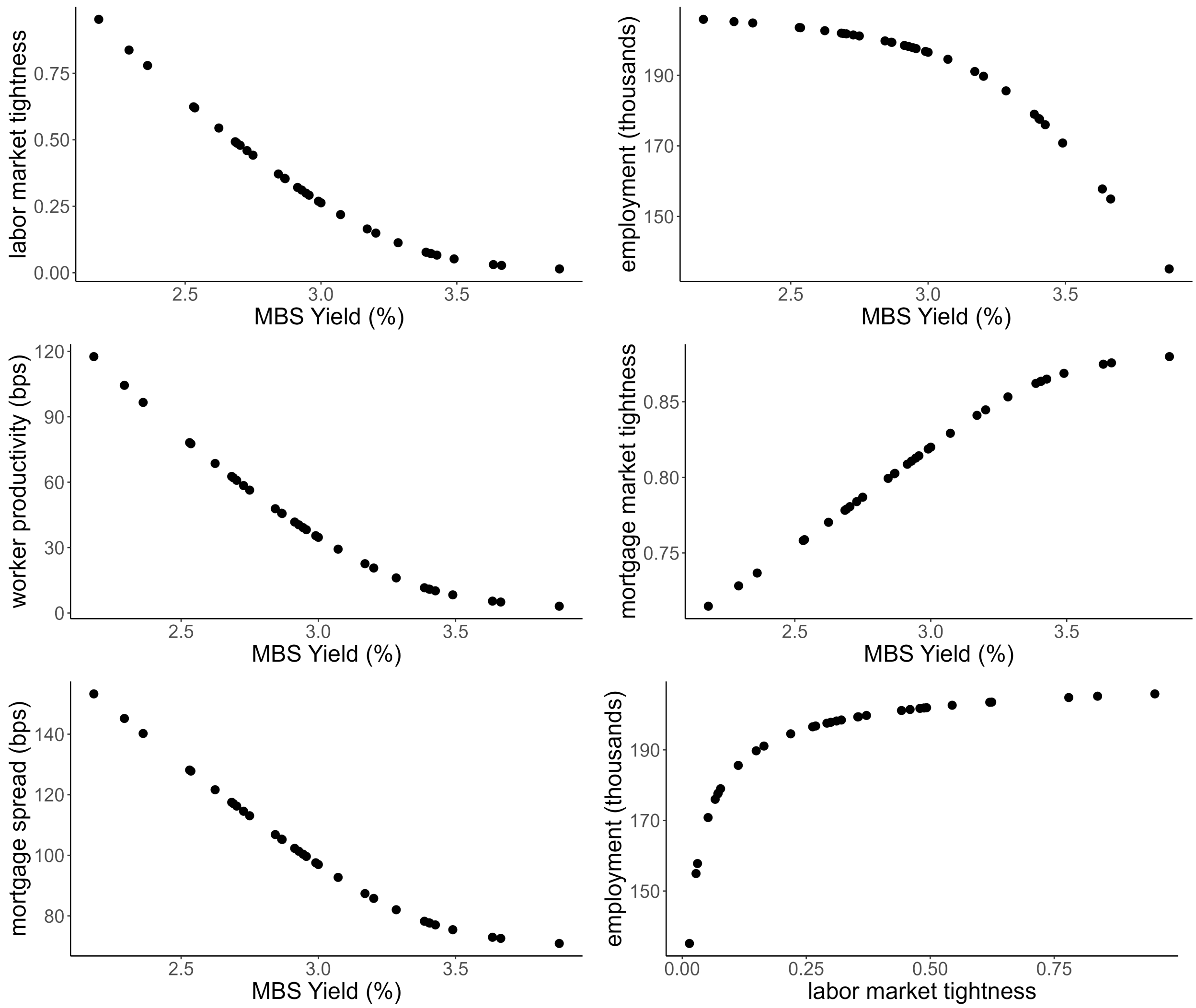
The figure plots the time series of the lender revenue multiplier calculated from the survey data and calibrated from the model. The survey data is calculated by dividing revenue per loan from the MBA Mortgage Bankers Performance Reports by mortgage spread. The model calibration does not use the survey data and the survey calculation does not use any model assumptions. The two series have a correlation of 0.81.

Figure 2.9: Forward Prediction



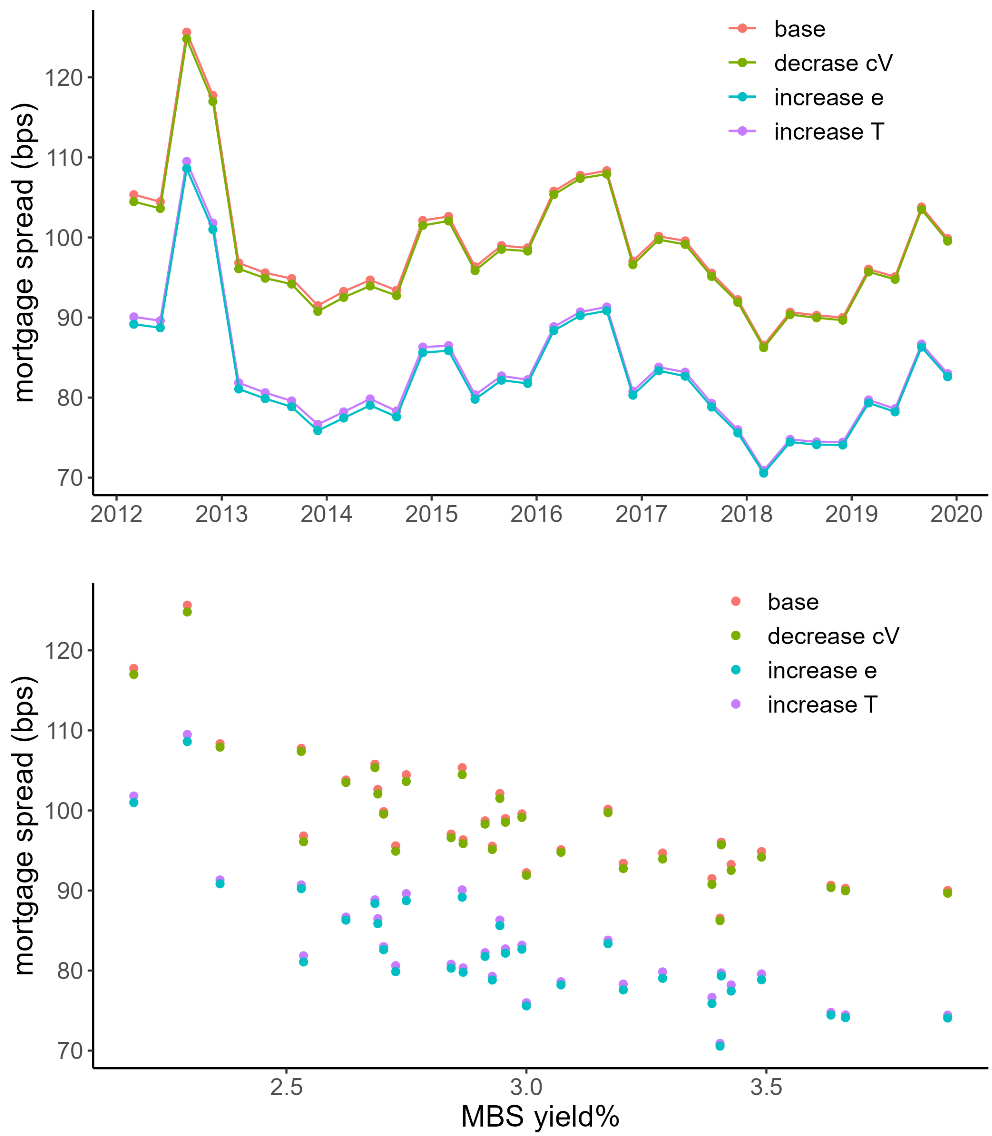
The figure plots the result for the exercise of forward prediction: using the calibrated parameters and labor supply at 2012Q1 to generate a predicted path for the period 2012Q2 to 2019Q4, given the actual path of MBS yield y. The first panel plots the time series of mortgage spread and the second panel plots mortgage spread against MBS yield, where the red dots are from the model's prediction and the blue dots are from the actual data. The third panel plots the model's predicted change in mortgage rate against the change in MBS yield, where the red (blue) dots are for periods when MBS yield is higher (lower) than its median.

Figure 2.10: Mechanism of Labor Market Frictions



This figure plots the model output of the forward prediction exercise, delving into the mechanism of the channel of labor market frictions. The first five panels plot different variables against MBS yield, including labor market tightness, employment, worker productivity, mortgage market tightness, and mortgage spread. The last panel plots employment against labor market tightness.

Figure 2.11: Counterfactuals



This figure shows the result of the three counterfactuals together with the base model: increasing labor supply by 20%, increasing worker efficiency by 20%, and reducing lender search cost for workers by 20%. The first panel plots the time series of predicted mortgage spreads. The second panel plots the predicted mortgage spread against MBS yield.

Table 2.1: Rate Dependency of Mortgage Rate Pass-through

Dependent Variable:	ΔMortgage Rate_t
Model:	(1)
Constant	-0.015*
	(-1.73)
ΔMBS Yield_t	0.788***
	(23.9)
Relative MBS Yield_t	0.039*
	(1.80)
ΔMBS Yield_t × Relative MBS Yield_t	0.347***
	(4.74)
Observations	32
R^2	0.96813
Adjusted R^2	0.96471

IID co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta\text{Mortgage Rate}_t = \beta_0 + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative MBS Yield}_t + \varepsilon_t$$

This table runs the above regression to estimate mortgage rate pass-through and its variation with the level of interest rates over the sample period from 2012Q1 to 2019Q4. ΔMortgage Rate_t is the quarterly change of mortgage rate, ΔMBS Yield_t is the quarterly change of MBS yield, and Relative MBS Yield_t is the difference between MBS yield at quarter t and the median MBS yield over the sample period. Data for mortgage rate is from the Freddie Mac's Primary Mortgage Market Survey. Data for MBS yield is the current coupon rate of 30-year Fannie Mae MBS from Bloomberg.

Table 2.2: Model Calibration

	Description	Value	Method
r	discount rate	0.0086	annual rate 3.5%
ρ	borrower revenue multiplier	25	annual rate 3.5%, 7 years
c^A	borrower search cost	29.7 bps	Agarwal, Grigsby, Hortaçsu, Matvos, Seru, and Yao (2020)
c^K	search cost for borrowers	10 bps	
c^V	search cost for workers	157 bps	Silva and Toledo (2009)
c^U	worker search cost	0 bps	
e	worker efficiency	12	max(originations per worker)
s	separation rate	2%	match mean of unemployment
δ	borrower origination fee	500 bps	5% of loan amount
ζ	lender origination cost	221 bps	total lender cost minus wage
a, b	borrower utility	10% $\uparrow$ in A, 13 bps $\downarrow$ in μ	$\mu_t = a + blog(A_t)$
τ, γ	mortgage market matching	$\tau = 0.63, \gamma = 1$	match mean and SD of originations
χ, η	labor market matching	$\chi = 0.64, \eta = 0.34$	match mean and SD of hires
α	borrower bargaining power	vary by time	match $\{m, w, \phi\}$ quarter by quarter
β	worker bargaining power	vary by time	match $\{m, w, \phi\}$ quarter by quarter
λ	lender revenue multiplier	vary by time	match $\{m, w, \phi\}$ quarter by quarter

This table summarizes the calibrated parameters in the model, including their descriptions, calibrated values, and methods used for calibration.

Table 2.3: Rate Dependency of Predicted Mortgage Rate Pass-through

Dependent Variable:	ΔPredicted Mortgage Rate$_t$
Model:	(1)
Constant	-0.013**
	(-2.08)
ΔMBS Yield$_t$	0.424***
	(18.1)
Relative MBS Yield$_t$	-0.002
	(-0.127)
ΔMBS Yield$_t$ $\times$ Relative MBS Yield$_t$	0.340***
	(6.59)
Observations	31
R^2	0.95145
Adjusted R^2	0.94606

IID co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta \text{Predicted Mortgage Rate}_t = \beta_0 + \beta_1 \Delta \text{MBS Yield}_t + \beta_2 \Delta \text{MBS Yield}_t \times \text{Relative MBS Yield}_t + \varepsilon_t$$

This table runs the above regression to estimate mortgage rate pass-through and its variation with the level of interest rates, using the result of the forward prediction. That is, using the calibrated parameters and actual labor supply at 2012Q1 to predict the outcomes from 2012Q2 to 2019Q4. ΔPredicted Mortgage Rate$_t$ is the quarterly change of mortgage rate predicted by the model, ΔMBS Yield$_t$ is the quarterly change of MBS yield, and Relative MBS Yield$_t$ is the difference between MBS yield at quarter t and the median MBS yield over the sample period. It is the same regression as in Table 2.1 but uses the model predicted mortgage rate on the left-hand side instead of the actual mortgage rate.

Table 2.4: Mortgage Rate Pass-through of Counterfactuals

Dependent Variable:	ΔPredicted Mortgage Rate$_t$			
	base	increase T	increase e	decrease cV
Model:	(1)	(2)	(3)	(4)
Constant	-0.019**	-0.018**	-0.018**	-0.018**
	(0.008)	(0.008)	(0.008)	(0.008)
ΔMBS Yield$_t$	0.800***	0.812***	0.812***	0.800***
	(0.030)	(0.028)	(0.028)	(0.030)
Relative MBS Yield$_t$	0.041**	0.040**	0.039**	0.041**
	(0.020)	(0.018)	(0.018)	(0.020)
ΔMBS Yield$_t$ $\times$ Relative MBS Yield$_t$	0.336***	0.318***	0.318***	0.335***
	(0.066)	(0.062)	(0.062)	(0.066)
Observations	31	31	31	31
R^2	0.97528	0.97842	0.97848	0.97532
Adjusted R^2	0.97253	0.97602	0.97609	0.97258

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\Delta\text{Model Mortgage Rate}_t = \beta_0 + \beta_1 \Delta\text{MBS Yield}_t + \beta_2 \Delta\text{MBS Yield}_t \times \text{Relative MBS Yield}_t + \varepsilon_t$$

This table runs the above regression to estimate mortgage rate pass-through and its variation with the level of interest rates from 2012Q1 to 2019Q4, using the outputs of the base model and the three counterfactuals (increasing labor supply by 20%, increasing worker efficiency by 20%, and reducing lender search cost for workers by 20%). ΔModel Mortgage Rate$_t$ is the quarterly change of mortgage rate solved from the model. ΔMBS Yield$_t$ is the quarterly change of MBS yield. Relative MBS Yield$_t$ is the difference of MBS yield at quarter t and the median MBS yield over the sample period.

Table 2.5: Economic Impact of Counterfactuals

	increase T	increase e	decrease cV
Rate impact (bps)	-15.9	-16.5	-0.5
PMT impact ($)	-18.3	-18.9	-0.6
FV impact ($)	-30,599	-31,665	-1,013

This table summarizes the economic impact of the three counterfactuals as compared to the base model: increasing labor supply by 20%, increasing worker efficiency by 20%, reducing lender search cost for workers by 20%. Assuming a 30-year fixed rate mortgage loan with a balance of 200K and a starting mortgage rate of 4%, the table shows the average impact on mortgage rate, monthly mortgage payment, and future value over the period from 2012Q1 to 2019Q4.

Table 2.6: Comparison of Counterfactuals

	base	increase T	increase e	decrease cV
m	3.972	3.813	3.807	3.967
ϕ	0.956	1.004	1.005	0.958
K	2.669	3.138	3.156	2.683
A	2.974	3.338	3.352	2.985
w	89.600	48.680	56.800	88.295
θ	1.038	0.555	0.655	1.288
x	90.200	49.168	57.321	88.823
U	8.980	16.124	12.200	7.849
T-U	221.199	260.091	217.980	222.330

This table summarizes key output variables of the model, where columns are for the base model and the three counterfactuals: increasing labor supply by 20%, increasing worker efficiency by 20%, and reducing lender search cost for workers by 20%. The rows are the average model outputs over the period from 2012Q1 to 2019Q4 for mortgage rate, mortgage market tightness, lender capacity, mortgage applications, labor market wage for mortgage industry workers, labor market tightness, worker productivity, unemployment, and employment.

2.7 Appendix

2.7.1 Mortgage Market Search Equilibrium

From Equation $((A_0)A_1)$ and free entry of borrowers $A_0 = 0$, we get

$$\frac{c^A}{g(\phi)} = A_1 = \rho(\mu(A) - m) - \delta$$

From Equation $(K_1)(K_0)$, we get

$$K_1 - K_0 = \frac{r\lambda(m - y) - r\zeta + c^K}{r + p(\phi)}$$

Then from Nash bargaining,

$$\begin{aligned}
&\frac{A_1 - A_0}{K_1 - K_0} \\
=& \frac{A_1}{K_1 - K_0} \\
=& \frac{c^A(r + p(\phi))}{(r\lambda(m - y) - r\zeta + c^K)g(\phi)} \\
=& \frac{\alpha}{1 - \alpha}
\end{aligned}$$

2.7.2 Labor Market Search Equilibrium

Given the law of motion for unemployment and $\frac{dU}{dt} = 0$, we derive the steady-state equation for unemployment

$$U = \frac{Ts}{s + f(\theta)}$$

From Equation $((V_0)V_1)$ and free entry of job vacancies $V_0 = 0$, we get

$$\frac{c^V}{q(\theta)} = V_1 = \frac{x - w}{r + s}$$

Then from Nash bargaining and the Bellman equations, we get

$$
\begin{aligned}
&(1-\beta)(rU_1 - rU_0) = \beta r V_1 \\
\Rightarrow &(1-\beta)(w + s(U_0 - U_1) - rU_0) = \beta(x - w + s(V_0 - V_1)) \\
\Rightarrow &(1-\beta)(w - rU_0) = \beta(x - w) \\
\Rightarrow &w = \beta x + (1-\beta) rU_0 \\
&\quad = \beta x + (1-\beta)(-c^U + f(\theta)(U_1 - U_0)) \\
&\quad = \beta x + (1-\beta)(-c^U + f(\theta)\frac{\beta}{1-\beta}\frac{c^V}{q(\theta)}) \\
&\quad = \beta(x + \theta c^V) - (1-\beta)c^U
\end{aligned}
$$

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CHAPTER 3

Nonbank Mortgage Servicers and Consumer Satisfaction

3.1 Introduction

In Chapter 1 and 2, I document the negative impact of lender operational capacity pressures on mortgage rate pass-through and find effective ways to improve mortgage rate pass-through should target to make the mortgage industry scalable in accommodating mortgage demand. The recent rapid growth of the nonbank sector partially helped this through leveraging technologies to streamline origination processes and filling in the supply gap of banks downsizing lending business due to stricter regulatory requirements. However, the growth of nonbanks has also sparked an intense debate over its potential consequences on consumers. This chapter focuses on the mortgage servicing market and explores the impact on borrowers from the growing market share of nonbank mortgage servicers [1].

Mortgage servicers play a central role in helping homeowners manage loans and keep homes, by collecting mortgage payments, maintaining escrow account, proposing loan modifications, or initiating foreclosures when borrowers become delinquent. Since the great financial crisis, the mortgage servicing market has seen a significant shift from bank to nonbank servicers, with the market share of nonbank servicers among the top 25 growing dramatically from 4.0% in 2008 to 42.3% in 2018 (Shoemaker (2019)). On the negative side, Lee (2014) questions whether nonbanks have adequate capacity to handle expanding servicing portfolios and whether they should face the same or different regulatory standards than banks given their higher sensitivity to market changes. On the positive side, Lux and Greene (2015)

[1] Nonbank mortgage servicers are companies doing mortgage servicing business, not taking deposits, and not associated with any depository institutions.

document nonbanks are acclaimed for leveraging technology to facilitate borrower education, streamline processes, predict defaults and design loss modification strategies, which improve customer experience and enable more delinquent borrowers to keep their homes. Given the importance of mortgage servicers, the continuous growth of nonbanks and the ongoing debate over the impact on consumers, this chapter provides insights by comparing bank and nonbank servicers in their performance to satisfy consumer needs, measured by the proportion of consumers filing complaints with the Consumer Financial Protection Bureau (CFPB).

Using a panel regression with complaint and servicing portfolio data from 2012 to 2019, I find a nonbank servicer receives one more complaint among approximately 270 borrowers than a bank servicer on average in one state and one quarter. The complaint data is from the CFPB, a government agency responsible for consumer protection in the financial sector, created by the Dodd-Frank Wall Street Reform and Consumer Protection Act passed in 2010[2]. The agency began collecting consumer complaints in late 2011 and established the CFPB complaint database, with the goal to expose problems consumers face and inform sound regulation policy. The servicing portfolio data is from Fannie Mae and Freddie Mac's Single-Family Loan Performance dataset, which includes loan acquisition and monthly performance snapshots for 30-year and less, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages. By combining the complaint data and servicing portfolio data, I calculate complaint ratios for each servicer and run a panel regression to compare servicers' performance between banks and nonbanks. The result shows nonbanks have higher complaint ratios than banks, implying the underperformance of nonbanks than banks in servicing borrowers.

However, an alternative explanation could be more difficulties associated with serving nonbank consumers. Buchak, Matvos, Piskorski, and Seru (2018) find nonbanks have more business in areas with larger minority groups and are more aggressive in servicing riskier, less creditworthy FHA borrowers. This does not necessarily mean nonbank consumers are more

[2] `https://www.consumerfinance.gov/about-us/the-bureau/creatingthebureau/`

difficult to serve, but banks and nonbanks do serve different groups of borrowers and the difference in consumer base may mask the true difference in servicer performance. For example, a company servicing low-income neighborhoods may receive more complaints because of heavier involvement in delinquencies and complex loan modification procedures, not because of its incapability to manage loans. To mitigate this concern, I add controls for borrower and loan characteristics serviced by each company, including average mortgage rate, unpaid principal balance, months to maturity, loan-to-value ratio, borrower credit score, proportion of refinance loans, and proportion of first-time home buyers. State-quarter fixed effects are also included to rule out demographic heterogeneity across states which can vary over time. In addition, I control for the volume of servicing transfers to rule out performance difference caused by capital market activities in buying and selling servicing assets.

The panel regression shows complaint ratios for nonbanks are on average 0.327% higher than banks, which is 1.7 times of the mean complaint ratio of the whole sample. However, 75% of the data points in the servicer-quarter-state level sample are zero complaint ratios, and the distribution of complaint ratio is right skewed. Given the large portion of zero complaint ratios, I run a linear probability regression to compare whether banks and nonbanks are more likely to have positive complaint ratios. Interestingly, the result shows nonbanks are 4.6% less likely to have positive complaint ratios, meaning they are more likely to be top performers without receiving any complaint. A panel regression conditional on the subsample with positive complaint ratios still shows nonbanks have complaint ratios that are 4 times higher than banks.

To further mitigate the concerns regarding unobserved borrower characteristics, I continue to present an instrument variable regression, using the average tier 1 risk-based capital ratios of banks servicing a particular area as an instrument for nonbank penetration in that area. The idea is to compare consumer complaint ratios in areas with different levels of nonbank servicer penetration predicted by an instrument which is independent of borrower characteristics in that area. The validity of this instrument is established by its strength in predicting nonbank penetration levels and the assumed exclusion restriction of its independence with borrower characteristics.

First, it strongly predicts nonbank penetration. Buchak, Matvos, Piskorski, and Seru (2018) show banks ceded more lending shares to nonbanks in areas where banks faced stricter capital and regulatory constraints. Similarly, I find higher penetration of nonbank servicers in areas where banks have higher capital ratios. One important factor driving the growth of nonbank servicers is the Basel III capital regime implemented in 2015 that significantly increases the cost of banks to hold servicing assets (Goodman and Lee (2014)). As banks downsize servicing portfolios to build capital buffers and increase capital ratios, nonbanks fill the gap and gain more servicing shares. Second, assuming banks make decisions to adjust capital ratios at a national level, which is independent of borrower characteristics in a local area, I argue that banks' capital ratios can only affect regional complaint ratios through affecting the penetration of nonbanks. Given the strength of the instrument and the assumed exclusion restriction, I still find higher complaint ratios in areas with higher predicted penetration of nonbank servicers, supporting the underperformance of nonbank servicers as compared to banks.

Aside from the overall underperformance of nonbanks, I also find their difference in complaint ratios persists through time without narrowing, even though regulators have issued new policies to regulate the entire mortgage servicing market. These new policies help reduce risks associated with the growing nonbank sector, which is traditionally not subject to the same level of federal supervision and capital requirement as banks. For example, the CFPB released new mortgage servicing rules in 2013 to implement provisions of the Dodd-Frank Wall Street Reform and Consumer Protection Act [3]; the Federal Housing Finance Agency (FHFA) implemented new financial eligibility rules in 2015, setting minimum capital, liquidity and net worth requirements for all Fannie Mae and Freddie Mac (the GSEs) servicers[4]. There are also new rules specifically targeting the nonbank sector. For example, the Conference of State Bank Supervisors (CSBS) proposed regulatory prudential standards

[3] https://www.consumerfinance.gov/policy-compliance/rulemaking/final-rules/mortgage-servicing-rules-under-real-estate-settlement-procedures-act-and-truth-lending-act/

[4] https://www.fhfa.gov/Media/PublicAffairs/Pages/New-Eligibility-Requirements-for-SellerServicers.aspx

for nonbank servicers in 2015[5]; Ginnie Mae revealed plans to stress test nonbank issuers in 2019[6]. Though we do see a decreasing trend of overall complaint ratios in the mortgage servicing market as greater supervision and regulation are implemented, I find the difference in complaint ratios between nonbank and bank servicers persists, indicating room for nonbank servicers to improve.

This chapter relates to the literature on the rise of nonbanks, their behaviors and potential risks they pose to the financial market. One factor contributing to the rise of nonbanks is regulatory arbitrage. Morris-Levenson, Sarama, and Ungerer (2017) examine the impact of tighter banking on the composition of lending market and find less-regulated bank and nonbank mortgage companies have grown faster in mortgage origination. Buchak, Matvos, Piskorski, and Seru (2018) find banks lost more market shares to nonbanks in markets where they faced more regulatory burdens. Many large banks also suffer from post-crisis litigation for crisis-era legacy portfolios while the GSEs facilitate nonbanks' originate-to-sell model (Shoemaker (2019)). Another factor driving the growth of nonbanks is technological innovation. Fuster, Plosser, Schnabl, and Vickery (2019) find FinTech lenders process mortgage applications faster, alleviate capacity constraints and facilitate refinance without increasing default rates. Buchak, Matvos, Piskorski, and Seru (2018) show online origination technology saves FinTech companies costs and provide them more efficient information for screening borrowers and setting prices.

With the growth of nonbanks also comes the consequences they bring to the financial market. On one hand, nonbanks opened up access to mortgage credit for a broader range of consumers such as riskier borrowers with lower credit scores. On the other hand, concerns arise about the deterioration of lending standards and higher risks to the financial system. Purnanandam (2011) shows the originate-to-distribute model of lending, which many nonbanks depend on, decreases originator's incentives to screen loans and result in more origination of inferior quality mortgages. Demyanyk and Loutskina (2016) find bank holding

[5]https://www.csbs.org/standards-non-bank-servicers-documents

[6]https://www.ginniemae.gov/newsroom/publications/Documents/ginniemae_rfi_stress_testing.pdf

companies circumvented regulations by lending through mortgage banking subsidiaries and originated mortgages to riskier borrowers, which contributed to the deterioration of lending standards and played a role in the 2007 credit crisis. Gete and Reher (2017) show that nonbanks are more sensitive to MBS liquidity and were drawn to the FHA market after the U.S. Liquidity Coverage Ratio (LCR) rule, which increased the credit risk borne by U.S. tax payers. Kim, Laufer, Pence, Stanton, and Wallace (2018) show nonbank companies are vulnerable to liquidity pressures in both loan origination and servicing activities due to limited funding resources, exposing the government to significant risks given their large shares in the FHA and VA loan market.

While many papers center on the mortgage origination market, this paper adds to the literature by focusing on the mortgage servicing market, where consumer protection has been a challenge because of the important role servicers play in helping homeowners keep homes and the potential misalignment of interests between servicers and borrowers. For example, Thompson (2011) shows servicers may favor foreclosure over modification because lacking ownership interest in loans even though modification is in borrowers' best interests. Like the origination market, the servicing market also sees a surge of nonbanks. High fines and legal fees with crisis-era servicing portfolios not only added to the servicing costs of banks who were active pre-crisis but also exposed many problems they had in servicing nonperforming loans. On the contrary, nonbanks may have cost advantage over banks in servicing nonperforming loans because they are smaller, less complex, have lower compliance costs, very few legacy exposure, and more experience in handling delinquencies (Kaul and Goodman (2020)). The Basel III capital regime in 2013 which assigned higher-risk weights to mortgage servicing assets also reduced banks' willingness to hold servicing assets (Goodman and Lee (2014)). With the migration of bank to nonbank servicers going on, it is therefore important to understand the potential consequences on consumers. Whether nonbanks improve consumer experience by using technology to streamline processes or harm consumers because of lacking robust compliance systems remains a question and this paper provides insights on this by looking directly at consumer complaint data.

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 introduces the panel regression. Section 4 presents the instrument variable regression. Section 5 compares nonbanks and banks over time. Section 6 concludes.

3.2 Data

3.2.1 Loan Performance Dataset

To calculate complaint ratio, which is the measure for consumer satisfaction that reflects servicer performance, we need both complaint data and servicing portfolio data. For servicing portfolio, I use Fannie Mae and Freddie Mac's Single-Family Loan Performance dataset due to its public access, broad coverage of the conventional mortgage market and rich details of borrower and loan characteristics. The loan performance dataset covers loans acquired by the GSEs that are 30-year-and-less, fully amortizing, full-documentation, single family, conventional and fixed-rate. The monthly performance snapshots from Fannie Mae include servicer name for each loan in every month. The loan acquisition snapshots from Freddie Mac include servicer name for each loan at origination. Though the dataset does not cover all the residential loans originated, it covers 36% of those reported in the Home Mortgage Disclosure Act (HMDA) data, which is the most comprehensive source of public data on the U.S. mortgage market. If considering only conventional loans, the loan performance dataset covers 47% of those reported in the HMDA data[7]. I focus on conventional loans because they conform to similar underwriting standards which makes unobserved soft information less a concern. Furthermore, the rich array of loan and borrower characteristics are used as controls to make the comparison between mortgage servicers more robust.

One concern of using the loan performance dataset is banks hold more loans on balance sheets than nonbanks and the loan performance dataset may represent different proportions of portfolios held by banks versus nonbanks. Buchak, Matvos, Piskorski, and Seru (2018) document that banks hold more than 30% of mortgages on balance sheets while nonbanks retain at most 7.5%. This concern is mitigated given the finding that nonbanks have higher

[7] This is based on the HMDA data and loan performance data from 2012 to 2017.

complaint ratios. Because one would expect banks to take more efforts in servicing loans on their balance sheets, nonbanks should underperform banks even more if we consider those loans banks hold on their balance sheets.

3.2.2 CFPB Complaint Database

For complaint data, I use the CFPB complaint database, which is a collection of consumer complaints about financial products and services. The CFPB complaint database includes complaints consumers submitted directly through website, phone, mail, email, fax, as well as complaints referred from the White House, congressional offices, federal agencies, and state agencies[8]. The total number of complaints is increasing every year, implying an increasing consumer awareness of the CFPB (Figure 3.2). When consumers file a complaint, they answer questions like what the complaint is about, what kind of mortgage (if they choose 'mortgage' in the first question), and what type of problem they encounter. As summarized in Table 3.1, 23% of all the complaints from 2012 to 2019 are for mortgages; within these mortgage complaints, 35% are for conventional fixed loans; within these conventional fixed loan complaints, 82.4% are for servicing issues. These numbers show a large portion of consumer complaints are for mortgage product and many borrowers are facing mortgage servicing issues. Each complaint record contains information about the date receiving the complaint, the property state of the consumer, the narrative of the complaint if provided, the date sending the complaint to the company for response, the response from the company, and very importantly, the company receiving this complaint. I focus on servicing complaints for conventional fixed loans to match with the loan performance data. By matching the complaint data and servicing portfolio data by company, I calculate complaint ratios for each mortgage servicer.

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[8] `https://www.regulations.gov/document?D=CFPB-2018-0014-0001`

3.2.3 Bank Call Reports

In the instrument variable regression, I use the average tier 1 risk-based capital ratio of banks servicing a particular area as an instrument for predicting the penetration of nonbank servicers in that area. Tier 1 risk-based capital ratio is the ratio of a bank's core equity capital to its total risk-weighted assets. Banks with higher tier 1 risk-based capital ratios have more capital buffers against adverse economic shocks. I use bank level tier 1 risk-based capital ratios reported by all U.S. regulated banks in their call reports filed with the Federal Deposit Insurance Corporation (FDIC) quarterly. To calculate the average capital ratio of banks servicing a particular area, I first find bank level capital ratios for each bank branch in the area from call reports and then calculate the average capital ratio weighted by the deposit share of each bank branch in that area in the previous year. The deposit data is from the Summary of Deposits, an annual survey of branch office deposits for FDIC-insured institutions, which is also included in the bank call reports.

3.2.4 Servicer Identification and Matching

Because different data sources may record the same servicer using different names, and the same data source may record the same servicer by different names at different times, I identify and match servicer names from different datasets manually, including servicer name in the loan performance dataset, company name in the CFPB complaint dataset, and bank name in the call reports. For companies belonging to the same parent organization, I identify them as the parent organization. For companies not existing today due to mergers and acquisitions, I identify them using archived website information. From each servicer's website, I determine whether the servicer is a bank or nonbank by checking if banking service information is described online. Nonbanks are companies not taking deposits and not associated with depository institutions. If a servicer provides banking service information on its website and the servicer is not a government agency or nonprofit organization, I categorize it as a bank. If a servicer is an independent mortgage company that does not provide any banking service, it is categorized as a bank or nonbank depending on whether it is affiliated with any depository institution.

In the loan performance dataset, companies that service less than 1% of the total current unpaid principal balance for the last month of a given quarter are recorded as 'Other'. Though these companies in aggregate service 40.4% of all the conventional single-family fixed rate loans acquired by the GSEs from 2012 to 2019, I do not include them in the analysis because they cannot be identified and their market size individually is small (Table 3.2). Excluding these 'Other' servicers, 53 servicers with a totaling market share of 59.6% are identified, among which 23 are banks and 30 are nonbanks. For these 53 servicers, I find no complaints for 5 banks, which have an aggregate market share of 0.25%; I also find no complaints for 9 nonbanks, which have an aggregate market share of 5.3%. One may be concerned that complaint numbers for some servicers are underestimated if we do not correctly identify them from the complaint database due to the challenge of matching company names. But this concern is mitigated given the finding that nonbanks have higher complaint ratios. As shown in Table 3.2, if there is a downward bias in complaint numbers, the bias is larger for nonbanks: there are more nonbanks for which I do not find complaints and these nonbanks take much larger market shares than the banks for which I do not find complaints; for most banks I do not find complaints, the servicing market share is less than 0.05%. Furthermore, it is more common for nonbanks to hire sub-servicers than banks and customers may complain against sub-servicers instead of the nonbank that holds the servicing assets, which will make the downward bias for nonbanks even greater.

3.3 Aggregate Complaint Trend

Before running regressions to investigate complaint ratios, we can first get some insights from Figure 3.3, which plots the aggregate time series of mortgage servicing complaints filed against banks versus nonbanks. Mortgage servicing complaints are complaints related to loan servicing, payment collection, escrow account, loan modification, foreclosure, and any other trouble during the payment process (see Table 3.1). Panel A plots the number of complaints (lines) and the number of loans in servicing portfolios (bars) of banks and nonbanks, and

Panel B plots complaint ratios of banks (red line) and nonbanks (blue line). [9]

The figure shows complaints have been decreasing for both banks and nonbanks. As shown in Panel A, though the servicing portfolio size for banks (nonbanks) increased from 3.2 millions (0.9 million) in 2014Q1 to 6.4 millions (4.7 millions) in 2018Q4, the number of complaints for banks (nonbanks) decreased from 1,410 (1,776) to 8,39 (1,253). This is consistent with Panel B, which shows the complaint ratio for banks (nonbanks) decreased from 0.044% (0.184%) to 0.013% (0.027%). The decreasing trend in complaint ratios implies an improvement of services provided by mortgage servicing companies over time, which is the outcome of continued efforts from policy makers to improve transparency of the mortgage market and educate borrowers to protect their rights.

Though complaint ratios have been decreasing for both banks and nonbanks, the figure also shows nonbanks always have higher complaint ratios than banks. As shown in Panel A, though nonbanks service fewer loans than banks, they receive more complaints than banks. For example, in 2014Q1, nonbanks received more complaints (1,776) than banks (1,410) but serviced fewer loans (0.9 million) than banks (3.2 million). This is consistent with Panel B, which shows the line of complaint ratio for nonbanks always lies above the line for banks, though the gap in between is shrinking. The reducing gap may be an outcome of efforts from policy makers in recent years to improve the regulatory framework and tools for the nonbank sector. However, without further analysis, we cannot conclude the reducing gap is due to improved performance of nonbanks versus banks. One alternative explanation could be nonbanks have started to serve more consumers with lower default risks, thus reducing the likelihood to receive complaints related to foreclosures and loan modifications.

3.4 Panel Regression

In this section, I compare complaint ratios between banks and nonbanks more precisely by using a panel regression. Though the general trends in the previous section show nonbanks

[9] Though the CFPB complaint data is available from 2012, I only include data after 2014 because the reported data in the early periods when the CFPB started collecting complaints are noisy.

have higher complaint ratios than banks, we can not conclude nonbanks underperform banks in providing good-quality services to mortgage borrowers because banks and nonbanks may serve very different customers. Banks and nonbanks may also grow with different paces over time which varies in terms of macroeconomic and regulatory conditions. By using a panel regression, I include controls for loan and borrower characteristics, as well as regional and time fixed effects, to rule out these alternative explanations.

In detail, I use the following regression specification

$$\text{ComplaintRatio}_{m,s,t} = \beta\, \text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t} \tag{3.1}$$

where the left-hand side is the complaint ratio of mortgage servicer m for its loans serviced in state s and quarter t. The dummy variable Nonbank_m indicates whether the mortgage servicer is a nonbank. $X_{m,s,t}$ is a vector of loan and borrower controls, including the average interest rate, months to maturity, loan-to-value ratio, unpaid principal balance, borrower credit score, portion of refinance loans, first-time home buyers and servicing transfers of the loans serviced by mortgage servicer m in state s and quarter t. $\alpha_{s,t}$ is state-quarter fixed effect.

Including control variables $X_{m,s,t}$ makes β closer to the true difference in complaint ratios resulted from servicer difference by removing observable confounds reflecting consumer difference. For example, a servicer with more first-time home buyers may receive fewer complaints because first-time home buyers do not have experience in interacting with mortgage servicers and may be less aware of the CFPB complaint system, not because the servicer is performing well in its servicing jobs; a servicer with more 15-year mortgage borrowers than 30-year mortgage borrowers may receive fewer complaints because consumers taking a shorter term mortgage may have more stable earnings to afford higher monthly payment thus may encounter less trouble in the mortgage payment process. The control for servicing transfers removes confounds reflecting capital market activity difference including buying and selling servicing assets. For example, a servicer may receive a lot of complaints because of issues from another party that is transferring servicing assets to it, not because the servicer is not fulfilling its own servicing tasks.

Including state-quarter fixed effect $\alpha_{s,t}$ removes state level confounds that can vary over time. For example, a servicer may receive more complaints because its main business is in a less developed region with more foreclosures, or its main business location experiences negative local economic shocks. In the end, the goal is to make β a measure of the difference in complaint ratio between nonbank and bank servicers within state, within quarter, and with similar consumers, so that it can reflect the true difference in servicer performance.

Table 3.3 compares observable characteristics between banks and nonbanks. The final sample includes 31,890 data points, covering 20 quarters from 2014 to 2019 and 53 states. The first line shows there are 16 banks and 29 nonbanks in the sample. The second line shows 41% of the data points (12,975) are for banks, and 59% (18,915) are for banks. The rest rows compare the average mortgage rate, loan term, loan-to-value ratio, credit score, loan balance, refinance share, first-time homebuyer share, and servicing transfer share between banks and nonbanks. All the differences are significant at 1% significance level. Nonbanks serve consumers with mortgage loans with higher interest rate, longer loan term, higher loan-to-value ratio, lower credit score, and higher loan balance. Nonbanks also have a higher share of first-time homebuyer consumers, a smaller share of refinance consumers, and more activities involving servicing asset transfers. Therefore, banks and nonbanks serve significantly different consumer populations and it is important to include these controls for loan and borrower characteristics in Regression (1.4) to compare complaint ratios between banks and nonbanks.

Table 3.4 reports summary statistics for the whole sample. The first row shows 75% of the sample has a zero complaint ratio and the distribution has a right tail, leading to a zero median, a mean of 0.22%, and a standard deviation of 1.54%. The second row shows positive complaint ratios have a median of 0.07%, a mean of 0.77%, and a standard deviation of 2.79%, which is still right-skewed. The third row shows the log transformation of positive complaint ratios is closer to be normally distributed. This is confirmed in Figure 3.4, where the left chart plots the histogram of complaint ratio and the right chart plots the histogram of its log transformation. Given these many zero data points and a right skewed distribution, I run the regression in three ways in the following analysis: first, I run a pooled regression using all the data points; second, I run a linear probability regression to investigate whether banks or nonbanks are more likely to have positive complaint ratios; third, I run a panel regression to compare log complaint ratios between these two groups conditional on them already receiving complaints, using the sub-sample of positive complaint ratios.

3.4.1 Pooled Regression

Table 3.5 reports the result for Regression (1.4) using the whole sample. Consistent with Figure 3.3, the table shows nonbank servicers have significantly higher complaint ratios than bank servicers, controlling for loan and borrower characteristics, as well as time-varying regional characteristics. The main result in Column (1) which includes quarter-state fixed effect shows complaint ratios for nonbanks are higher by 0.372% on average than banks. This is 24% of the standard deviation of complaint ratios and 1.7 times of the mean complaint ratio of the whole sample. Economically, this means a nonbank servicer receives 1 more complaint among 270 borrowers each quarter within a state than a bank servicer who serves similar consumers and operates within similar environment. Column (2) to (4) use different fixed effects and show similar result as Column (1). All standard errors are clustered by state and quarter.

We also see statistical and economic significance for several control variables: when mortgage rate increases by 10 bps, complaint ratio is estimated to decrease by 0.1%; when loan term increases by 10 years, complaint ratio is estimated to increase by 0.17%; when loan-to-value ratio increases by 10%, complaint ratio is estimated to decrease by 0.36%; when loan balance increases by 100K, complaint ratio is estimated to decrease by 0.54%; when the company serves 10% more first-time homebuyers, its complaint ratio is estimated to decrease by 0.16%. One hypothesis explaining the negative coefficient of interest rate could be borrowers able to get lower rate mortgages are higher-income, more creditworthy, and more educated about ways to protect their rights, thus being more likely to file complaints. One hypothesis explaining the negative coefficient of first-time home buyers could be first-time home buyers are less experienced in coping with mortgage servicers and are less knowledgeable about ways to file complaints. One hypothesis explaining the positive coefficient for loan term and negative coefficient for loan balance could be borrowers taking shorter term and higher balance mortgages are more likely to have more stable income, can afford higher monthly payment, have less difficulty in paying mortgage, thus being less likely to complain.

3.4.2 Linear Probability Regression

Table 3.6 reports summary statistics for the two sub-samples depending on whether complaint ratio is positive. As shown in the table, 9,184 data points have positive complaint ratios and 22,706 data points have zero complaint ratios. The table shows the sub-sample with zero complaint ratios has 62% nonbanks and the other sub-sample with positive complaint ratios has 52% nonbanks. Given the large proportion of zero complaint ratios, in this section, I run a linear probability regression to compare the likelihood of receiving any complaint between banks and nonbanks.

Instead of predicting the magnitude of complaint ratios, I run the following regression to predict whether complaint ratio is positive

$$\text{PositiveComplaint}_{m,s,t} = \beta\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t} \tag{3.2}$$

where the left hand side variable is a dummy variable indicating whether mortgage servicer m received any complaint in state s and quarter t. The rest variables are the same as in Equation 3.1.

Table 3.7 shows nonbanks are less likely to have positive complaint ratios, meaning nonbanks are more likely to receive no complaints at all. The main result in Column (1) shows nonbanks are 4.6% less likely to have positive complaint ratios, after controlling for observable loan and borrower characteristics, within quarter and within state. Column (2) to (4) which include different fixed effects show similar results. All standard errors are clustered by quarter and state. The likelihood for positive complaint ratios for a servicer also increases by 3% when its average borrower loan balance increases by 10K, or average share of first-time homebuyers increases by 10%.

This result is interesting and concealed by a simple pooled regression. Though overall nonbanks have higher complaint ratios, there are actually more nonbanks that receive zero complaints. This implies performance heterogeneity in nonbanks: some nonbanks perform really well and receive zero complaints; some nonbanks perform poorly and receive more complaints than banks servicing similar consumers.

3.4.3 Regression Conditional on Receiving Complaints

The previous section shows nonbanks are more likely to receive no complaints at all and this section answers whether banks or nonbanks have higher complaint ratios, conditional on both receiving nonzero complaints.

Panel A in Table 3.6 reports summary statistics of the sub-sample with nonzero complaints, which is the sample for the regression in this section. The first line shows nonzero complaint ratio has a median of 0.07%, a mean of 0.77%, and a standard deviation of 2.79%, whose distribution is right skewed. As shown in Figure 3.4, log transformation makes the distribution more normally distributed. Therefore, I run the following regression to more accurately estimate the difference in complaint ratios between banks and nonbanks, conditional on both having positive complaint ratios

$$\log(\text{PositiveComplaintRatio})_{m,s,t} = \beta\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t} \tag{3.3}$$

where the left hand side variable is a log transformation of positive complaint ratios.

Table 3.8 shows conditional on receiving complaints, nonbanks have higher complaint ratios than banks significantly. Given the median complaint ratio of 0.03% for banks with positive complaint ratios, the main result in Column (1) predicts the complaint ratio of a nonbank serving similar customers in the same quarter and same state is 0.15%[10], which is 4 times higher. If using the mean complaint ratio of 0.17% for banks with positive complaint

[10] $exp(log(0.03) + 1.6) = 0.15$

ratios, the result predicts the complaint ratio of a nonbank is 0.84%[11], which is also 4 times higher. Column (2) to (4) include different fixed effects and show similar results. All standard errors are clustered by quarter and state. The coefficient estimation of 1.6 for the nonbank dummy is 83% of the standard deviation of $\log(\text{PositiveComplaintRatio})_{m,s,t}$ in the data.

To sum up, the panel regression shows interesting comparisons between banks and nonbanks in providing satisfying services to their customers. First, using a pooled regression with the whole sample, I find nonbanks' complaint ratio is 0.372% higher than banks, controlling for observable loan and borrower characteristics and including quarter-state fixed effect. Second, using a linear probability model, I find nonbanks are 4.6% less likely to have positive complaint ratios. Third, using the sub-sample with positive complaint ratios, I find nonbanks' complaint ratio is 4 times higher than banks. The result shows nonbanks have higher complaint ratios than banks overall, but nonbanks are also more likely to be top performers with zero complaints.

3.5 Instrument Variable Regression

Though the panel regression includes many controls and fixed effects to identify the difference between banks and nonbanks in serving similar consumers, there could still be omitted confounds such as unobserved borrower characteristics that could affect complaint ratios. To relieve this concern, in this section, I present an instrument variable regression, using the regional heterogeneity of banks' tier 1 risk capital ratios as an instrument for the regional penetration of nonbank servicers and then compare the complaint ratios of areas with different levels of nonbank servicer penetration. If nonbanks underperform banks in servicing borrowers, we would expect to see higher complaint ratios in areas with higher predicted market share of nonbank servicers.

The validity of this instrument is established by its strength to predict nonbank servicer penetration and the assumed exclusive restriction of its independence of regional borrower

[11] $exp(log(0.17) + 1.6) = 0.84$

characteristics that can affect complaint ratios. Buchak, Matvos, Piskorski, and Seru (2018) show regulatory arbitrage contributed to the rise of shadow banks and banks' tier 1 risk capital ratios could predict the market share of nonbank lenders in the mortgage origination market. Similarly for the mortgage servicing market, I conjecture banks' capital ratios can predict the penetration of nonbank servicers. For example, Basel III bank capital standards, adopted by US regulators in 2013, significantly increased the cost of holding mortgage servicing assets on balance sheets so many large banks downsized servicing portfolios to increase capital buffers (Goodman and Lee (2014)) and lost market shares to nonbank servicers.

As for exclusive restriction, I assume banks' decisions on capital ratios are mainly driven by the regulatory burden and capital constraints they face at the national level, which are irrelevant of regional borrower characteristics that can affect complaint ratios, thus arguing that banks' capital ratios are correlated to regional complaint ratios only through the correlation with nonbank servicer penetrations. Hence, I run a first-stage regression to predict nonbank servicer penetration in each area using the average capital ratio of banks servicing that particular area weighted by each bank's deposit share in that area in the previous year, then run a second-stage regression to compare complaint ratios in areas with different levels of predicted nonbank servicer penetration. Given the strength and exclusive restriction of the instrument, this instrument variable regression attempts to identify the difference in complaint ratios between banks and nonbanks uncorrelated to the difference in their consumer base.

Specifically, I run the following first-stage regression:

$$\text{NonbankServicingMarketShare}_{s,t} = \beta_1 \, \text{BankCapitalRatio}_{s,t} + \Gamma X_{s,t} + \alpha_s + \gamma_t + \epsilon_{s,t} \tag{3.4}$$

where

$$\text{BankCapitalRatio}_{s,t} = \sum_{b \in s,\, b \in i} \text{BankCapitalRatio}_{i,t} * \text{BankDepositShare}_{b,s,t-1} \tag{3.5}$$

$\text{NonbankServicingMarketShare}_{s,t}$ is the servicing market share of nonbanks in state s and quarter t. $\text{BankCapitalRatio}_{s,t}$ is the weighted average tier 1 risk capital ratios of all banks in state s and quarter t, with weights equal to the deposit share of bank branch b in state s in the previous year. That is, for every branch b in state s that belongs to bank i, I multiply the capital ratio of bank i in quarter t by the deposit share of branch b in state s in the previous year and then sum over for all branches in the state to calculate this average capital ratio of banks in state s and quarter t. $X_{s,t}$ is a vector of loan and borrower controls, including the average interest rate, months to maturity, loan-to-value ratio, unpaid principal balance, borrower credit score, portion of refinance loans, and first-time home buyers of the loans in state s and quarter t. State fixed effect and quarter fixed effect are added to control for time-invariant state characteristics and macro time trends that can affect the penetration of nonbank servicers.

Table 3.9 reports summary statistics of the sample, which has 990 data points, covering 20 quarters from 2014 to 2019 and 50 states. The first row shows complaint ratio across state and quarter has a median of 0.022%, a mean of 0.029%, and a standard deviation of 0.022%. The second row shows average bank capital ratio has a mean of 12.6% and a standard deviation of 0.9%. The third row shows nonbank servicing market share has a mean of 30.42% and a standard deviation of 8.73%. The rest rows show summary statistics for the other control variables, including average mortgage rate, loan term years, loan-to-value ratio, credit score, loan balance, refinance share, and first-home buyer share.

Table 3.10 reports the first-stage result, which shows when average local bank capital ratio increases by 1%, nonbank servicing market share in the area increases by 0.9%, which is 10% of the standard deviation of nonbank servicers' market shares (8.7%). State and quarter fixed effects are included and standard errors are clustered by state and quarter. The partial F-statistics for local bank capital ratio in the regression is 61, verifying its strength in predicting nonbank servicing market share. Figure 3.5 plots nonbank servicing market share against local bank capital ratio and shows a positive correlation between these two variables.

Then I run the following second-stage regression:

$$\text{ComplaintRatio}_{s,t} = \beta_2\,\text{NonbankServi}\widehat{\text{cing}}\text{MarketShare}_{s,t} + \Gamma X_{s,t} + \alpha_s + \gamma_t + \epsilon_{s,t} \tag{3.6}$$

where $\text{ComplaintRatio}_{s,t}$ is the complaint ratio of state s at quarter t. On the right-hand side, $\text{NonbankServi}\widehat{\text{cing}}\text{MarketShare}_{s,t}$ is the predicted nonbank servicing market share of state s at quarter t from the first-stage regression. $X_{s,t}$ are the same set of controls as in the first-stage regression. α_s, γ_t are state and quarter fixed effects.

Table 3.11 reports the second-stage result, which shows when nonbank servicing market share increases by one standard deviation (8.73%), complaint ratio in the same state and quarter increases by 0.036%[12], which is 1.6 times of the standard deviation of complaint ratios across state and quarter (0.022). State and quarter fixed effects are included and standard errors are clustered by state and quarter. The significant difference in complaint ratios between areas with different levels of predicted nonbank servicer penetration shown here is consistent with the result shown in the panel regression, both indicating the under-performance of nonbanks compared to banks in servicing borrowers. Given this result and the continued shift of servicing from traditional bank servicers to nonbank servicers, the challenge for consumer protection in the mortgage servicing market is worth attention.

3.6 Comparison Over Time

In this section, I examine whether the performance difference between banks and nonbanks varies over time by allowing the coefficient in regression (3.1) to change over time and run the following regression:

$$ComplaintRatio_{m,s,t} = \beta_t\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t} \tag{3.7}$$

[12] 8.73%*0.0041=0.036%

where β_t measures the difference between nonbank servicers and bank servicers in complaint ratios at quarter t.

Figure 3.6 shows the result of the estimated coefficient β_t and its 99% confidence interval. As shown in the figure, nonbanks underperform banks in almost every quarter and the difference in their complaint ratios is not decreasing with time but slightly increasing with time. Though the overall complaint ratio has decreased a lot in recent years with the implementation of more comprehensive rules and stricter standards in the mortgage servicing market, the difference in complaint ratios between nonbank and bank servicers persists. This might be caused by greater challenge in regulating the nonbank sector, which is not traditionally subject to the same standards as depository institutions. For example, depository institutions have long been subject to well-versed stress testing oversight by the Federal Reserve, FDIC, Office of the Comptroller of the Currency (OCC) and National Credit Union Administration (NCUA), while Ginnie Mae only recently issued stress testing plans for nonbanks in 2019[13]. The greater challenge in regulating nonbanks also means greater room in improving services provided by nonbanks to borrowers, which will benefit consumers with the continuing shift of mortgage servicing from banks to nonbanks. The persistent underperformance of nonbank mortgage servicers in satisfying consumers may also be caused by their different business focus and incentives as compared to banks, which deserves further study to help make effective policy decisions.

3.7 Conclusion

The nonbank sector has taken an increasing market share of the loan origination and servicing business in recent years. At the end of 2018, six of the ten largest servicers were nonbanks[14]. A rising literature is studying what causes the rise of nonbanks and what impact nonbanks may bring to the mortgage market. With a goal to shed light on the impact nonbanks

[13] https://www.ginniemae.gov/newsroom/publications/Documents/ginniemae_rfi_stress_testing.pdf

[14] https://www.consumerfinance.gov/data-research/research-reports/data-point-servicer-size-mortgage-market/

may bring to consumers in the mortgage servicing market, this paper compares the levels of consumer satisfaction between nonbank and bank servicers, measured by complaint ratios using the number of complaints filed with the CFPB and the servicing portfolio data from Fannie Mae and Freddie Mac's loan performance dataset.

I find consumers are less satisfied with nonbank servicers than with bank servicers. First, in a panel regression, after controlling for loan and borrower characteristics, a nonbank servicer receives one more complaint among 270 consumers on average within state and within quarter. Second, in an instrument variable regression, regions where nonbank servicers take 8.73% (1 standard deviation) more market share predicted by higher average bank capital ratios have 0.036% (1.6 standard deviations) higher complaint ratios. The instrument variable regression provides a cleaner identification against confounds related to unobserved borrower characteristics.

Furthermore, splitting the sample into positive complaint ratios and zero complaint ratios. I find nonbanks are 4.6% more likely to be a top performer with zero complaint. Conditional on receiving complaints, nonbanks still have complaint ratios that are four times higher than banks. This implies heterogeneity within the nonbank sector. Top performing nonbanks could increase consumer welfare through bringing more technological advances, market competition, and high-quality service. But nonbanks providing less satisfying services could pose a risk to consumers, given the less mature regulatory frameworks for the nonbank sector.

Regulators and policymakers have taken great efforts to regulate both the bank and nonbank servicers to bring greater protection to consumers. Since the release of new mortgage servicing rules in 2013, complaint ratio of the entire mortgage servicing market has been decreasing every year. However, this paper shows the gap in complaint ratios between nonbanks and banks persists. An area of further research is to investigate why nonbanks are underperforming banks in servicing borrowers. Possible reasons could be: nonbanks are less capitalized thus lacking resources to build better infrastructures to service loans; nonbanks hire sub-servicers who have fewer incentives to meet customer needs; nonbanks are less regulated and more difficult to supervise, etc. By understanding the reasons behind, we can think of strategies to help nonbanks improve. This has important implications on consumers as the shift from bank to nonbank servicers continues in the future.

In conclusion, the U.S. mortgage market has been experiencing great changes in the recent decade: more comprehensive and mature regulatory frameworks, more national and competitive markets, more exposed problems of operational capacity pressures in the low rate environment, as well as improved awareness of the importance to upgrade old-fashioned lending platforms and manual workflows into high-tech efficient solutions. The burgeoning nonbanks, especially fintech companies, bring exciting opportunities to digitalize lending and improve mortgage rate pass-through. In the meantime, efforts should be taken to supervise the growth of this nonbank sector, avoiding negative consequences and taking full advantage of it to maximize consumer welfare.

Figure 3.1: CFPB Complaint Snapshot

3113055

Date CFPB received the complaint
12/30/2018

Consumer's state
CA

Consumer's zip

Submitted via
Web

Tags

Did consumer dispute the response?
N/A

Product
Mortgage
Sub-product: Conventional home mortgage

Issue
Trouble during payment process

Consumer consent to publish narrative
Consent provided

Consumer complaint narrative
In late XXXX I received Nationstar/Mr. Cooper XXXX Statement for {$1100.00} & balance of {$97000.00} XX/XX/2018, mailed XXXX Check # XXXX, {$97000.00} to Nationstar/Mr. Cooper XX/XX/2018 Nationstar/Mr. Cooper deposited check in XXXX XXXX Account # XXXX XXXX payment of {$1100.00} was due by XX/XX/2018 XX/XX/2018 Nationstar/Mr. Cooper reported my account delinquent to XXXX, XXXX and XXXX Credit Reporting Agencies while in possession of {$97000.00}, labeled my Nationstar/Mr. Cooper Account Delinquent and charged a late fee of {$56.00}. It took 35 days for Nationstar/Mr. Cooper to refund my {$97000.00}, with additional interest charge of {$8.00} per day, an additional 7-day hold placed on Nationstar/Mr. Coopers check by XXXX before I could access the {$97000.00} and re-start the process. This took a total of 45 days. TIMELINE BREAKDOWN OF THE {$97000.00} XX/XX/18 Friday : Nationstar Deposits Funds XX/XX/18 Thursday : Nationstar Returns Funds to me (via XXXX) XX/XX/18 Saturday : I Deposit Funds, but they are held until XX/XX/18 XX/XX/18 Friday : Total Funds Available XX/XX/18 Friday : Nationstar Receives {$98000.00} The Payoff Amount for XX/XX/2018 was {$98000.00}. The Payoff Amount for XX/XX/2018 was {$98000.00} This 42 day time frame of my {$97000.00} being unavailable increased my interest charge by {$250.00}. XX/XX/18 Payoff {$98000.00} XX/XX/18 Payoff {$98000.00} = {$250.00} Attachment 1 Nationstar/Mr. Cooper XXXX Payment Statement Attachment 2 Cancelled XXXX Check XXXX Attachment 3 Nationstar/Mr. Cooper Payment Activity Please view the two Posted Payments date XX/XX/18 Attachment 4 Merged Credit Report Attachment 5 Nationstar/Mr. Cooper Loan History Please view Transactions XXXX XXXX Attachment 6 XXXX Deposit Slip

Company information

Date complaint sent to company
12/30/2018

Company name
NATIONSTAR MORTGAGE

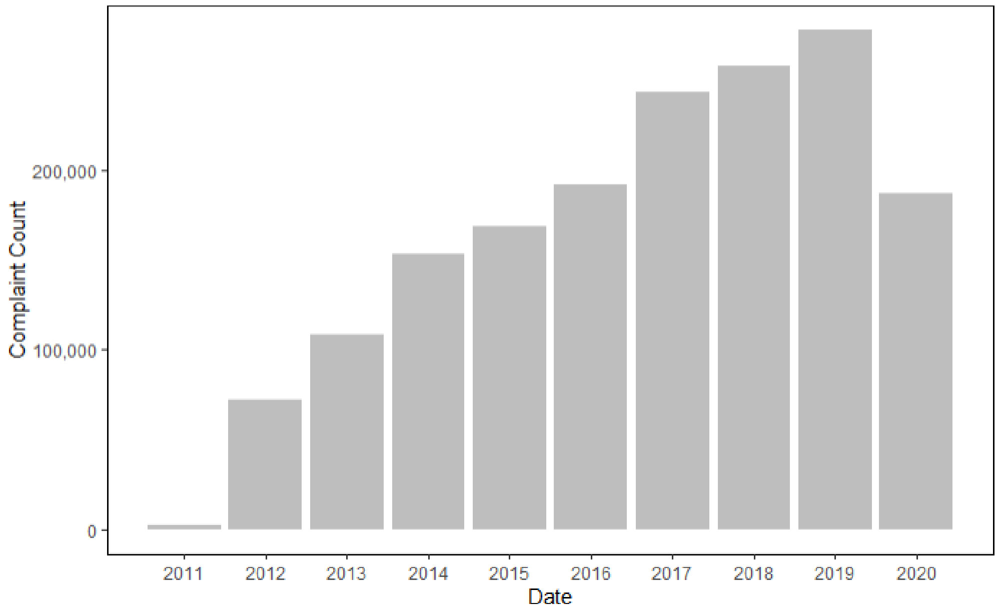
Timely response?
Yes

Company response to consumer
Closed with explanation

Company public response

This figure shows an example of consumer complaint reported by the CFPB Complaint Database. The complaint data includes information about the date CFPB received the complaint, the consumer's location, the product and issue of the complaint, the channel this complaint was submitted by, the company this consumer complained about, how did the company respond to the complaint, as well as the complaint narrative if the consumer consented to publish it.

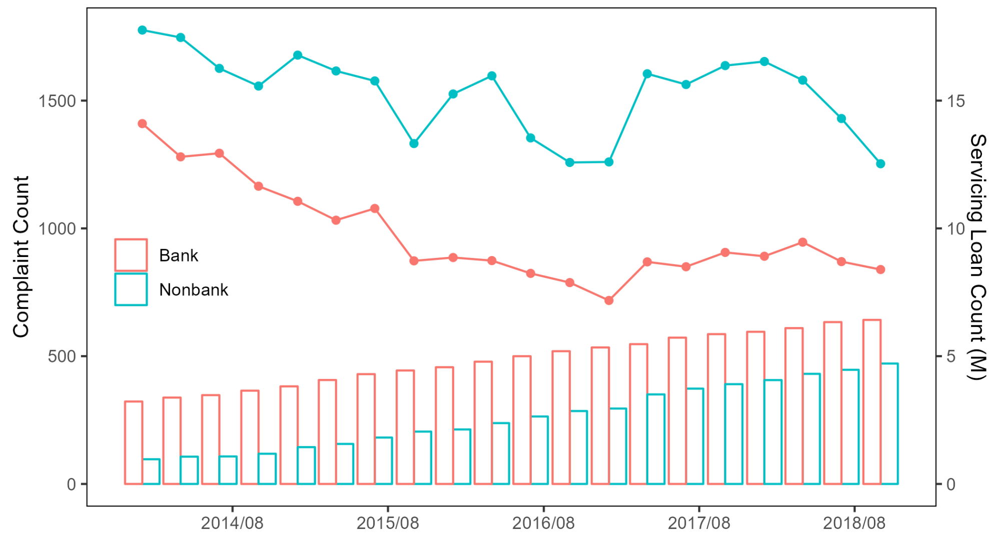
Figure 3.2: CFPB Total Complaints



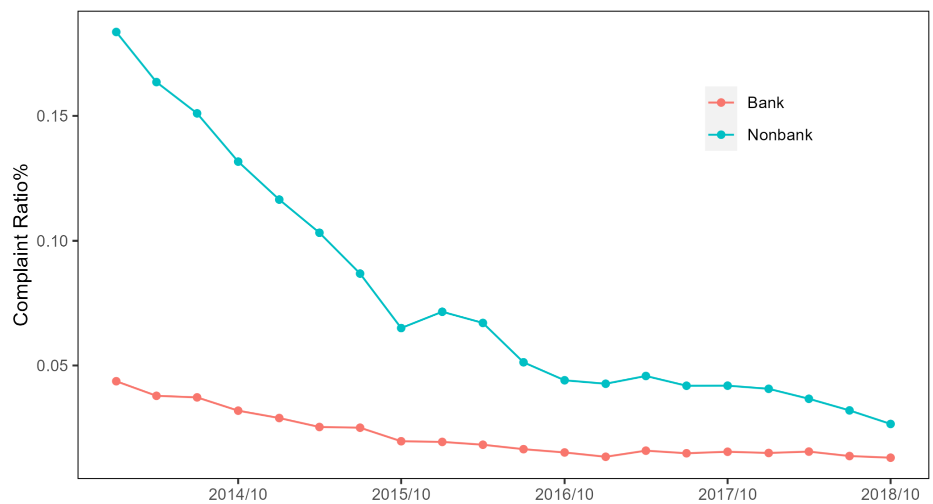
This figure plots the total number of consumer complaints submitted to the CFPB each year from 2011 to 2020. The data is obtained in August 2020 so the last bar covers only Jan to July in 2020.

Figure 3.3: Servicing Complaint Trend

Panel A: Complaint Count and Portfolio Size

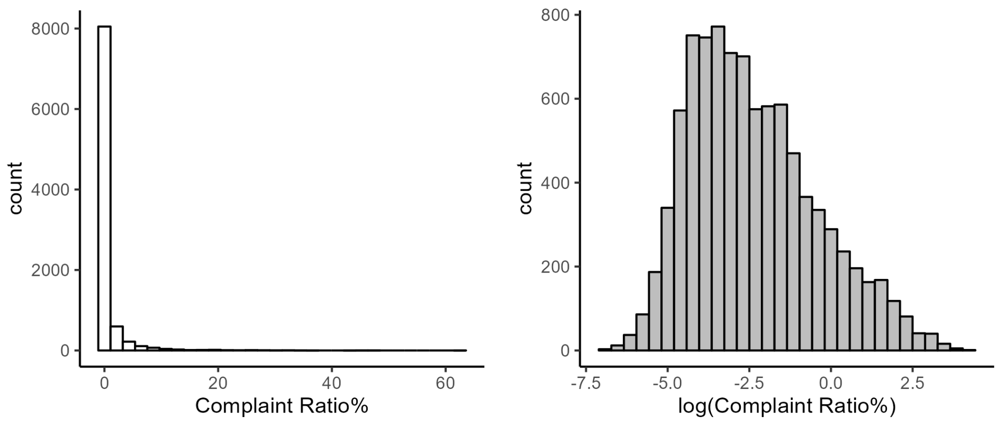


Panel B: Complaint Ratio



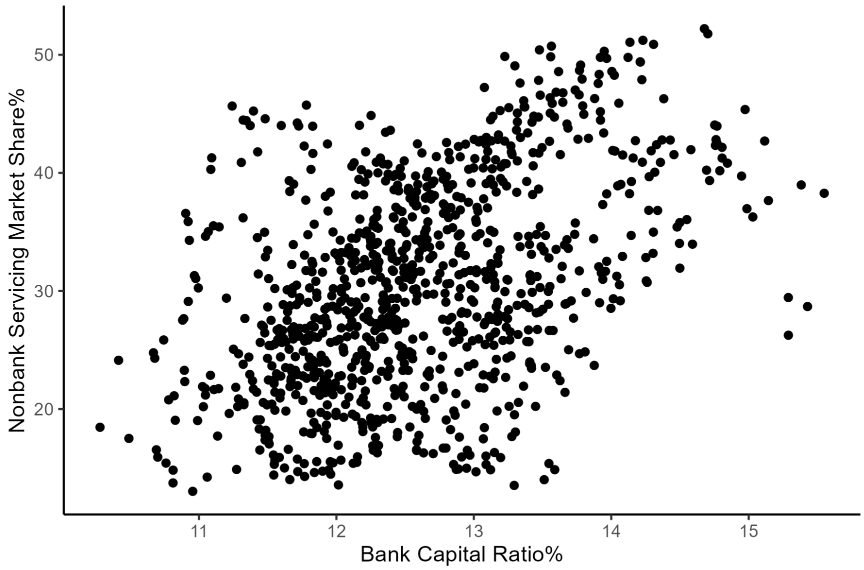
This figure plots the trend of mortgage servicing related complaints submitted to the CFPB against banks versus nonbanks. In Panel A, the red (blue) line is the number of conventional mortgage servicing complaints filed against banks (nonbanks) each quarter. The red (blue) bar is the number of conventional loans (in thousands) serviced by banks (nonbanks) each quarter. In Panel B, the red (blue) line is the complaint ratio (the number of complaints over the number of loans serviced) for banks (nonbanks). The data for complaints is from the CFPB Complaint Database and the data for servicing portfolio is from Fannie Mae and Freddie Mac's Loan Performance Dataset.

Figure 3.4: Histogram of Positive Complaint Ratios



This figure plots the histogram of servicing-related complaint ratios for conventional mortgage loans in the servicer-state-quarter level sample for all the servicers from 2014 to 2019. The left chart is the histogram of the complaint ratios and the right chart is the histogram of the log of complaint ratios for nonzero complaint ratios. The data for complaints is from the CFPB Complaint Database and the data for servicing portfolio is from Fannie Mae and Freddie Mac's Loan Performance Dataset. Complaint ratio is the ratio of the number of complaints over the number of loans in the servicing portfolio.

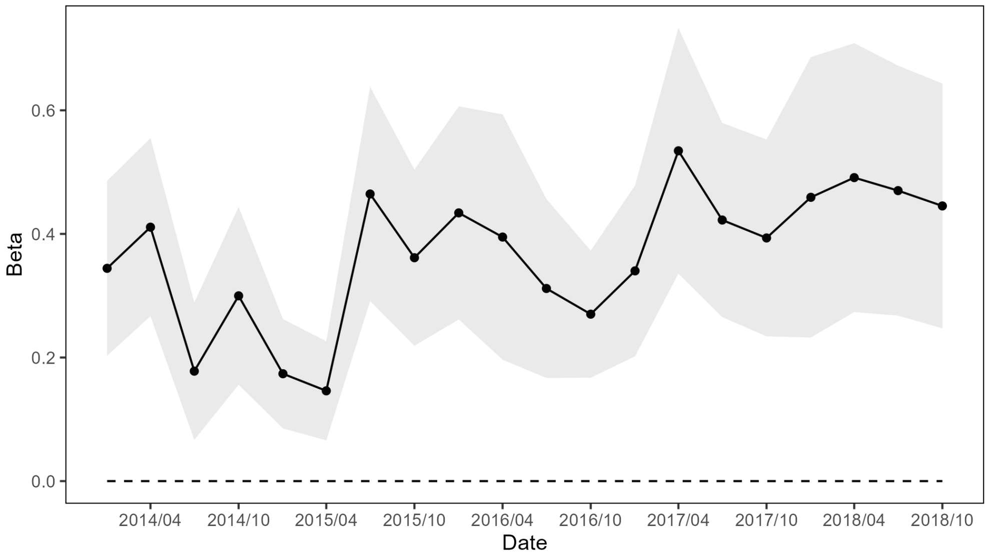
Figure 3.5: IV Regression First-Stage



$$\text{BankCapitalRatio}_{s,t} = \sum_{b \in s,\, b \in i} \text{BankCapitalRatio}_{i,t} * \text{BankDepositShare}_{b,s,t-1}$$

This figure plots the market share of nonbank servicers in the mortgage servicing market against the local bank capital ratio in the quarter-state level. In the first-stage regression, I use local bank capital ratios to predict nonbank servicing portfolio market shares. Local bank capital ratio is the weighted average capital ratio of banks in a region, with the weight being each bank branch's deposit share in the region in the previous year. As shown in the equation, $\text{BankCapitalRatio}_{i,t}$ is the capital ratio of bank i in quarter t, and $\text{BankDepositShare}_{b,s,t-1}$ is the deposit share of branch b (which belongs to bank i) in state s in the previous year. Data for bank capital ratios and deposit shares are from bank call reports published by the FDIC.

Figure 3.6: Comparison Over Time



$$\text{ComplaintRatio}_{m,s,t} = \beta_t \,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t}$$

This figure plots the estimated coefficient β_t and its confidence interval of the above regression. The black line is the estimated coefficient measuring the difference in complaint ratio between nonbanks and banks on average each quarter. The gray area is the 99% confidence interval of the coefficient. $\text{ComplaintRatio}_{m,s,t}$ is the complaint ratio of loans for a specific servicer in a specific state at a specific quarter. $X_{m,s,t}$ include the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, proportion of first-home buyers, and proportion of servicing transfers of the servicing portfolio of the servicer in the specific state and quarter. $\alpha_{s,t}$ is the state-quarter fixed effect. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset, and consumer complaint data comes from the CFPB.

Table 3.1: CFPB Complaint Issues

	What is this complaint about?	% of All
1	**Mortgage**	**22.57**
2	Debt collection	19.23
3	Credit reporting/repair services/reports	15.50
4	Credit reporting	11.76
5	Credit card	7.37
6	Bank account or service	7.22
7	Student loan	4.08
8	Credit card or prepaid card	3.32
9	Checking or savings account	2.85
10	Consumer Loan	2.65
11	Vehicle loan or lease	0.80
12	Money transfer/virtual currency/money service	0.73
13	Payday loan, title loan, or personal loan	0.61
14	Payday loan	0.46
15	Money transfers	0.45
16	Prepaid card	0.32
17	Other financial service	0.09
18	Virtual currency	0.00

	What kind of mortgage?	% of Mortgage
1	Other mortgage	32.01
2	**Conventional fixed mortgage**	**26.03**
3	FHA mortgage	11.29
4	Conventional adjustable mortgage (ARM)	9.34
5	**Conventional home mortgage**	**9.04**
6	Home equity loan or line of credit	4.29
7	Other type of mortgage	2.97
8	VA mortgage	2.64
9	Home equity loan or line of credit (HELOC)	1.12
10	Reverse mortgage	1.02
11	Second mortgage	0.25

	What type of problems are you having?	% of Conventional Mortgage
1	**Loan servicing, payments, escrow account**	**31.29**
2	**Loan modification,collection,foreclosure**	**29.75**
3	**Trouble during payment process**	**11.39**
4	**Struggling to pay mortgage**	**9.97**
5	Application, originator, mortgage broker	7.23
6	Settlement process and costs	3.51
7	Credit decision / Underwriting	2.33
8	Applying for a mortgage or refinancing	2.21
9	Closing on a mortgage	1.54
10	Incorrect information on your report	0.48
11	Other	0.11
12	Problem with a credit reporting company	0.11
13	Improper use of your report	0.03
14	Unable to get your credit report or credit score	0.02
15	Credit monitoring or identity theft protection	0.01
16	Problem with fraud alerts or security freezes	0.00

This table shows the three questions the CFPB website asks consumers when they submit complaints online and the associated product and issue options the CFPB provides for consumers to select from. Product and issue options used to identify servicing-related complaints are highlighted in bold. 22.57% of all consumer complaints are about mortgage; 35% of these mortgage complaints are about conventional fixed loans; 82.4% of these conventional fixed mortgage complaints are servicing-related issues. Data is from the CFPB Complaint Database and covers the period from 2012 to 2019.

Table 3.2: Complaints for Mortgage Servicers

	FirmName	FirmType	ServicingShare%	ComplaintCount
1	OTHER	Unknown	40.36	
2	WELLS FARGO BANK, N.A.	Bank	14.45	7846
3	JPMORGAN CHASE BANK, NATIONAL ASSOCIATION	Bank	5.05	4381
4	QUICKEN LOANS INC.	Nonbank	4.64	195
5	U.S. BANK N.A.	Bank	3.15	1281
6	SUNTRUST BANK	Bank	2.95	776
7	NEW RESIDENTIAL MORTGAGE LLC	Nonbank	2.73	896
8	MATRIX FINANCIAL SERVICES CORPORATION	**Nonbank**	2.53	
9	PNC BANK, N.A.	Bank	2.20	1285
10	PINGORA LOAN SERVICING, LLC	**Nonbank**	1.79	
11	NATIONSTAR MORTGAGE, LLC	Nonbank	1.68	7903
12	PENNYMAC CORP.	Nonbank	1.64	427
13	FREEDOM MORTGAGE CORP.	Nonbank	1.60	503
14	CALIBER HOME LOANS, INC.	Nonbank	1.43	1065
15	TRUIST BANK	Bank	1.33	268
16	BANK OF AMERICA, N.A.	Bank	1.31	8841
17	FLAGSTAR BANK, FSB	Bank	1.28	451
18	ROUNDPOINT MORTGAGE SERVICING CORPORATION	Nonbank	1.09	486
19	LAKEVIEW LOAN SERVICING, LLC	Nonbank	1.08	63
20	PROVIDENT FUNDING ASSOCIATES, L.P.	Nonbank	0.97	168
21	CITIZENS BANK, NATIONAL ASSOCIATION	Bank	0.96	290
22	CITIBANK, N.A.	Bank	0.86	2586
23	SENECA MORTGAGE SERVICING LLC	**Nonbank**	0.67	
24	DITECH FINANCIAL LLC	Nonbank	0.63	5356
25	FIFTH THIRD BANK	Bank	0.58	339
26	PHH MORTGAGE CORPORATION	Nonbank	0.55	738
27	AMERIHOME MORTGAGE COMPANY, LLC	Nonbank	0.31	127
28	OCWEN LOAN SERVICING, LLC	Nonbank	0.26	8521
29	GREEN TREE SERVICING, LLC	**Nonbank**	0.23	
30	ALLY BANK	Bank	0.22	4
31	ARVEST BANK GROUP, INC.	Bank	0.21	138
32	FEDERAL HOME LOAN BANK OF CHICAGO	**Bank**	0.13	
33	SPECIALIZED LOAN SERVICING LLC	Nonbank	0.13	1312
34	UNITED SHORE FINANCIAL SERVICES, LLC	Nonbank	0.10	66
35	HOME POINT FINANCIAL CORPORATION	Nonbank	0.10	78
36	USAA	Bank	0.10	52
37	AURORA FINANCIAL GROUP, INC.	Nonbank	0.09	7
38	REGIONS BANK	Bank	0.08	105
39	NEW YORK COMMUNITY BANK	Bank	0.08	70
40	GUILD MORTGAGE COMPANY	Nonbank	0.06	26
41	UNION SAVINGS BANK	**Bank**	0.05	
42	TIAA, FSB	Bank	0.05	286
43	STEARNS LENDING, LLC	**Nonbank**	0.05	
44	PODIUM MORTGAGE CAPITAL LLC	Nonbank	0.04	5
45	COLONIAL SAVINGS FA	**Bank**	0.04	
46	LOANDEPOT.COM, LLC	**Nonbank**	0.04	
47	IMPAC MORTGAGE CORP.	Nonbank	0.03	24
48	MUFG UNION BANK, N.A.	Bank	0.03	24
49	COLORADO FEDERAL SAVINGS BANK	**Bank**	0.02	
50	RUSHMORE LOAN MANAGEMENT SERVICES, LLC	Nonbank	0.01	656
51	METLIFE BANK, N.A.	**Bank**	0.01	
52	PAM MSR TRUST 1, LLC	**Nonbank**	0.01	
53	CENTRAL MORTGAGE COMPANY	**Nonbank**	0.01	
54	GMAC MORTGAGE, LLC	**Nonbank**	0.00	

This table shows the servicing market share and total number of complaints for all servicers identified from the GSEs' loan performance dataset and the CFPB complaint database from 2012 to 2019. Servicers for which no complaint data is found are highlighted in bold.

Table 3.3: Banks vs Nonbanks

	Bank	Nonbank	Diff
N Firm	16	29	13
N	12,975	18,915	5,940
$\text{OrigRate}_{m,s,t}$(%)	3.79	3.98	0.19
$\text{OrigLoanTerm}_{m,s,t}$(years)	25.73	26.72	0.99
$\text{OrigLTV}_{m,s,t}$(%)	74.21	75.78	1.57
$\text{OrigCreditScore}_{m,s,t}$	759.83	754.28	-5.55
$\text{OrigAvgUpb10k}_{m,s,t}$	21.05	22.17	1.12
$\text{RefiPct}_{m,s,t}$(%)	56.90	52.51	-4.39
$\text{FirstHomePct}_{m,s,t}$(%)	14.32	15.24	0.92
$\text{SrvTransferPct}_{m,s,t}$(%)	0.12	1.16	1.04

This table compares the means of observable loan and borrower characteristics of the servicing portfolios between banks and nonbanks in the servicer-state-quarter level sample from 2014 to 2019. The first row shows the number of banks and nonbanks. The second row shows the number of data points for banks and nonbanks. The third row shows the average mortgage rate of loans in the servicing portfolio for banks versus nonbanks. The rest rows show the average loan term in years, loan-to-value ratio, credit score, loan balance, share of refinance loans, share of first-time homebuyers, and share of servicing transferred loans. The third column shows the difference between nonbanks and banks. All the differences are significant at the 1% confidence level. Data is from the GSE's Loan Performance dataset.

Table 3.4: Summary Statistics (Pooled Regression)

	N	Mean	SD	Min	Q25	Q50	Q75	Max
ComplaintRatio$_{m,s,t}$(%)	31,890	0.22	1.54	0.00	0.00	0.00	0.01	62.50
PositiveComplaintRatio$_{m,s,t}$(%)	31,890	0.77	2.79	0.00	0.02	0.07	0.31	62.50
log(PositiveComplaintRatio)$_{m,s,t}$(%)	31,890	-2.38	1.94	-7.01	-3.87	-2.67	-1.16	4.14
NonbankDummy$_m$	31,890	0.59	0.49	0.00	0.00	1.00	1.00	1.00
OrigRate$_{m,s,t}$(%)	31,890	3.90	0.28	2.89	3.73	3.87	4.05	5.13
OrigLoanTerm$_{m,s,t}$(years)	31,890	26.32	2.21	13.36	25.09	26.50	27.86	30.00
OrigLTV$_{m,s,t}$(%)	31,890	75.14	4.82	46.92	72.17	75.74	78.52	89.88
OrigCreditScore$_{m,s,t}$	31,890	757	11	681	750	757	763	906
OrigAvgUpb10k$_{m,s,t}$	31,890	21.7	5.3	9.1	18.0	20.6	24.1	49.9
RefiPct$_{m,s,t}$(%)	31,890	54.3	18.2	0.0	41.3	53.3	66.4	100.0
FirstHomePct$_{m,s,t}$(%)	31,890	14.9	8.1	0.0	8.9	14.4	20.0	72.7
SrvTransferPct$_{m,s,t}$(%)	31,890	0.7	5.4	0.0	0.0	0.0	0.0	100.0

This table reports summary statistics of the servicer-state-quarter level sample from 2014 to 2019. The first row shows statistics for complaint ratios across servicer m, state s, and quarter t. The second row shows statistics for positive complaint ratios. The third row shows statistics for log complaint ratios. The fourth row shows 59% of the sample are data points for nonbanks. The rest rows show statistics for average mortgage rate, loan term, loan-to-value ratio, credit score, loan balance, share of refinance loans, share of first-time homebuyers, and share of servicing transferred loans. The sample includes 31,890 points, covering 20 quarters and 53 states. Servicing portfolio data is from the GSE's Loan Performance Dataset and complaint data is from the CFPB Complaint Database.

Table 3.5: Pooled Regression

Dependent Variable:	Complaint Ratio%			
Model:	(1)	(2)	(3)	(4)
NonbankDummy	0.372***	0.373***	0.368***	0.392***
	(0.019)	(0.056)	(0.055)	(0.037)
OrigRate	-1.03***	-1.03***	-0.966***	-1.07***
	(0.086)	(0.251)	(0.234)	(0.215)
OrigLoanTerm	0.017***	0.017***	0.016***	0.014***
	(0.002)	(0.004)	(0.003)	(0.005)
OrigLtv	-0.036***	-0.035**	-0.038**	-0.045***
	(0.007)	(0.017)	(0.017)	(0.007)
OrigCreditScore	-0.009***	-0.008**	-0.009**	-0.010***
	(0.002)	(0.004)	(0.004)	(0.002)
OrigAvgUpb10k	-0.054***	-0.055***	-0.051***	-0.043***
	(0.004)	(0.013)	(0.012)	(0.010)
RefiPct	0.004***	0.004	0.004	0.003
	(0.001)	(0.003)	(0.003)	(0.002)
FirstHomePct	-0.016***	-0.016**	-0.014*	-0.002
	(0.003)	(0.008)	(0.008)	(0.002)
SrvTransferPct	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Region-Date	Yes			
Region		Yes	Yes	
Date		Yes		Yes
Observations	31,890	31,890	31,890	31,890
R^2	0.07813	0.06570	0.06296	0.04419
Within R^2	0.05257	0.05183	0.05036	0.04288

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\text{ComplaintRatio}_{m,s,t} = \beta\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t}$$

This table shows the result of the above panel regression. $\text{ComplaintRatio}_{m,s,t}$ is the complaint ratio of loans for a specific servicer in a specific state at a specific quarter. $X_{m,s,t}$ includes the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, proportion of first-home buyers, proportion of servicing transfers of the servicing portfolio of the servicer in the specific state and quarter. $\alpha_{s,t}$ is the state-quarter fixed effect. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset, and consumer complaint data comes from the CFPB. The sample includes 31,890 points, covering 20 quarters from 2014 to 2019, 53 states, 16 banks, and 29 nonbanks. The variable of interest is β, which measures the difference in complaint ratio between a nonbank and bank servicer. All standard errors are clustered by state and quarter.

Table 3.6: Summary Statistics: Nonzero vs. Zero Complaint

Panel A: Nonzero Complaints

	N	Mean	SD	Min	Q25	Q50	Q75	Max
$\text{ComplaintRatio}_{m,s,t}(\%)$	9,184	0.77	2.79	0.00	0.02	0.07	0.31	62.50
$\log(\text{PositiveComplaintRatio})_{m,s,t}(\%)$	9,184	-2.38	1.94	-7.01	-3.87	-2.67	-1.16	4.14
NonbankDummy_m	9,184	0.52	0.50	0.00	0.00	1.00	1.00	1.00
$\text{OrigRate}_{m,s,t}(\%)$	9,184	3.86	0.19	2.90	3.75	3.84	3.96	4.90
$\text{OrigLoanTerm}_{m,s,t}(\text{years})$	9,184	25.91	2.05	14.26	24.89	26.15	27.20	30.00
$\text{OrigLTV}_{m,s,t}(\%)$	9,184	73.86	4.30	54.47	71.38	74.38	76.86	87.62
$\text{OrigCreditScore}_{m,s,t}$	9,184	758	8	700	753	759	764	783
$\text{OrigAvgUpb10k}_{m,s,t}$	9,184	21.7	5.0	9.8	18.1	20.7	24.6	43.0
$\text{RefiPct}_{m,s,t}(\%)$	9,184	57.0	14.7	9.9	47.1	57.1	67.2	100.0
$\text{FirstHomePct}_{m,s,t}(\%)$	9,184	14.4	7.1	0.0	9.3	13.8	18.7	67.0
$\text{SrvTransferPct}_{m,s,t}(\%)$	9,184	0.9	4.7	0.0	0.0	0.0	0.0	100.0

Panel B: Zero Complaint

	N	Mean	SD	Min	Q25	Q50	Q75	Max
$\text{ComplaintRatio}_{m,s,t}(\%)$	22,706	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NonbankDummy_m	22,706	0.62	0.49	0.00	0.00	1.00	1.00	1.00
$\text{OrigRate}_{m,s,t}(\%)$	22,706	3.91	0.31	2.89	3.72	3.89	4.10	5.13
$\text{OrigLoanTerm}_{m,s,t}(\text{years})$	22,706	26.48	2.25	13.36	25.17	26.69	28.16	30.00
$\text{OrigLTV}_{m,s,t}(\%)$	22,706	75.66	4.92	46.92	72.68	76.35	79.18	89.88
$\text{OrigCreditScore}_{m,s,t}$	22,706	756	11	681	749	756	763	906
$\text{OrigAvgUpb10k}_{m,s,t}$	22,706	21.7	5.4	9.1	18.0	20.6	24.0	49.9
$\text{RefiPct}_{m,s,t}(\%)$	22,706	53.2	19.4	0.0	39.2	51.0	65.5	100.0
$\text{FirstHomePct}_{m,s,t}(\%)$	22,706	15.1	8.5	0.0	8.7	14.8	20.7	72.7
$\text{SrvTransferPct}_{m,s,t}(\%)$	22,706	0.7	5.7	0.0	0.0	0.0	0.0	100.0

This table reports summary statistics of the two sub-samples depending on whether complaint ratios are zero. Panel A shows 9,184 (29%) of the data points have positive complaint ratios and Panel B shows 22,706 (71%) of the data points have zero complaint ratios. The first row shows statistics for complaint ratios across servicer m, state s, and quarter t. The second row in Panel A shows statistics for log complaint ratios. The third row in Panel A shows among the data with nonzero complaints, 52% are nonbanks. The second row in Panel B shows among the data with zero complaints, 62% are nonbanks. The rest rows show statistics for average mortgage rate, loan term, loan-to-value ratio, credit score, loan balance, share of refinance loans, share of first-time homebuyers, and share of servicing transferred loans. The whole sample includes 31,890 points, covering 20 quarters from 2014 to 2019 and 53 states. Servicing portfolio data is from the GSE's Loan Performance Dataset and complaint data is from the CFPB Complaint Database.

Table 3.7: Linear Probability Regression

Dependent Variable:	Positive Complaint Ratio			
Model:	(1)	(2)	(3)	(4)
NonbankDummy	-0.046***	-0.047***	-0.046***	-0.044***
	(0.013)	(0.013)	(0.013)	(0.013)
OrigRate	0.059	0.058	0.051	0.104*
	(0.037)	(0.036)	(0.032)	(0.053)
OrigLoanTerm	-0.0007	-0.0006	-0.0006	-0.001
	(0.0005)	(0.0005)	(0.0004)	(0.0007)
OrigLtv	-0.005	-0.004	-0.005	-0.027***
	(0.004)	(0.004)	(0.004)	(0.006)
OrigCreditScore	0.002***	0.002***	0.002***	0.0009
	(0.0006)	(0.0006)	(0.0005)	(0.001)
OrigAvgUpb10k	-0.033***	-0.032***	-0.032***	-0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
RefiPct	-0.0004	-0.0002	-0.0002	-0.0009
	(0.0007)	(0.0007)	(0.0007)	(0.001)
FirstHomePct	-0.003**	-0.003**	-0.003*	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)
SrvTransferPct	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Region-Date	Yes			
Region		Yes	Yes	
Date		Yes		Yes
Observations	31,890	31,890	31,890	31,890
R^2	0.18071	0.16515	0.16406	0.05049
Within R^2	0.06427	0.06283	0.06387	0.04823

Clustered (Region & Date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\text{PositiveComplaint}_{m,s,t} = \beta\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t}$$

This table shows the result of the above panel regression. $\text{PositiveComplaint}_{m,s,t}$ is a dummy variable indicating whether complaint ratio for a specific servicer in a specific state at a specific quarter is positive. $X_{m,s,t}$ includes the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, proportion of first-home buyers, proportion of servicing transfers of the servicing portfolio of the servicer in the specific state and quarter. $\alpha_{s,t}$ is the state-quarter fixed effect. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset, and consumer complaint data comes from the CFPB. The sample includes 31,890 points, covering 20 quarters from 2014 to 2019, 53 states, 16 banks, and 29 nonbanks. The variable of interest is β, which measures the difference in likelihood to receive complaints between a nonbank and bank servicer. All standard errors are clustered by state and quarter.

Table 3.8: Regression Conditional on Nonzero Complaints

Dependent Variable:	log(Complaint Ratio%)			
Model:	(1)	(2)	(3)	(4)
NonbankDummy	1.61***	1.59***	1.61***	1.59***
	(0.110)	(0.105)	(0.110)	(0.109)
OrigRate	-2.66***	-2.63***	-2.33***	-2.80***
	(0.700)	(0.690)	(0.721)	(0.777)
OrigLoanTerm	0.024**	0.023**	0.019*	0.022**
	(0.009)	(0.009)	(0.009)	(0.009)
OrigLtv	-0.058*	-0.052	-0.045	-0.035
	(0.033)	(0.032)	(0.033)	(0.026)
OrigCreditScore	-0.076***	-0.074***	-0.061***	-0.070***
	(0.010)	(0.009)	(0.009)	(0.010)
OrigAvgUpb10k	-0.046	-0.052*	-0.056*	-0.070**
	(0.030)	(0.029)	(0.030)	(0.027)
RefiPct	0.014	0.012	0.011	0.015*
	(0.009)	(0.008)	(0.008)	(0.008)
FirstHomePct	-0.046**	-0.048***	-0.058***	-0.029*
	(0.016)	(0.016)	(0.017)	(0.014)
SrvTransferPct	0.008	0.007	0.006	0.009
	(0.009)	(0.008)	(0.009)	(0.009)
Region-Date	Yes			
Region		Yes	Yes	
Date		Yes		Yes
Observations	9,184	9,184	9,184	9,184
R^2	0.43440	0.39511	0.37138	0.32300
Within R^2	0.34968	0.33596	0.32289	0.30859

Clustered (Region & Date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\log(\text{PositiveComplaintRatio})_{m,s,t} = \beta\,\text{Nonbank}_m + \Gamma X_{m,s,t} + \alpha_{s,t} + \epsilon_{m,s,t}$$

This table shows the result of the above panel regression using the sub-sample with positive complaint ratios. $\log(\text{PositiveComplaintRatio})_{m,s,t}$ is the log complaint ratio for a specific servicer in a specific state at a specific quarter. $X_{m,s,t}$ includes the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, proportion of first-home buyers, proportion of servicing transfers of the servicing portfolio of the servicer in the specific state and quarter. $\alpha_{s,t}$ is the state-quarter fixed effect. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset, and consumer complaint data comes from the CFPB. The sample includes 9,184 points, covering 20 quarters from 2014 to 2019, 53 states, 14 banks, and 20 nonbanks. The variable of interest is β, which measures the difference in log complaint ratio between a nonbank and bank servicer. All standard errors are clustered by state and quarter.

Table 3.9: **Summary Statistics (IV Regression)**

	Mean	SD	Min	Q25	Q50	Q75	Max
$\text{ComplaintRatio}_{s,t}(\%)$	0.029	0.022	0.000	0.014	0.022	0.038	0.156
$\text{BankCapitalRatio}_{s,t}(\%)$	12.60	0.90	10.28	11.94	12.49	13.16	15.55
$\text{NonbankServicingMarketShare}_{s,t}(\%)$	30.42	8.73	13.03	23.63	29.85	36.95	52.21
$\text{OrigRate}_{s,t}(\%)$	3.85	0.09	3.55	3.79	3.84	3.89	4.29
$\text{OrigLoanTerm}_{s,t}(\text{years})$	25.99	0.80	22.69	25.51	25.99	26.48	27.94
$\text{OrigLTV}_{s,t}(\%)$	74.78	2.84	64.42	73.44	75.46	76.76	79.94
$\text{OrigCreditScore}_{s,t}$	760	5	747	757	760	763	771
$\text{OrigAvgUpb10k}_{s,t}$	20.7	4.3	15.2	17.5	19.7	22.2	36.5
$\text{RefiPct}_{s,t}(\%)$	56.6	7.0	34.8	52.3	56.5	61.1	75.3
$\text{FirstHomePct}_{s,t}(\%)$	14.5	3.7	5.4	11.7	14.1	16.6	26.8

This table reports summary statistics of the sample for the instrument variable regression. The sample includes 990 data points, covering 20 quarters from 2014 to 2019 and 50 states. The first row reports statistics for complaint ratios across state s and quarter t. The second row reports statistics for local bank capital ratios. The third row reports statistics for market shares of nonbank mortgage servicers. The rest rows report statistics for average mortgage rate, loan term, loan-to-value ratio, credit score, loan balance, share of refinance loans, and share of first-time homebuyers. Local bank capital ratio is the weighted average capital ratio of banks in a region, with the weight being each bank branch's deposit share in the region in the previous year. Data for servicing portfolios is from the GSE's Loan Performance Dataset. Data for complaint is from the CFPB Complaint Database. Data for bank capital ratios and deposit shares is from banks' call reports.

Table 3.10: IV Regression First-Stage

Dependent Variable:	NonbankServicingMarketShare%
Model:	(1)
LocalBank CapitalRatio%	0.930***
	(0.265)
OrigRate	2.49
	(6.63)
OrigLoanTerm	0.096
	(0.105)
OrigLtv	0.701*
	(0.365)
OrigCreditScore	-0.086
	(0.171)
OrigAvgUpb10k	1.53***
	(0.502)
RefiPct	-0.091
	(0.149)
FirstHomePct	-0.976***
	(0.236)
Date	Yes
Region	Yes
Observations	990
R^2	0.98989
Within R^2	0.27642

Clustered (Date & Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\text{NonbankServicingMarketShare}_{s,t} = \beta_1 \, \text{BankCapitalRatio}_{s,t} + \Gamma X_{s,t} + \alpha_s + \gamma_t + \epsilon_{s,t}$$

where $\text{BankCapitalRatio}_{s,t} = \sum_{b \in s,\, b \in i} \text{BankCapitalRatio}_{i,t} * \text{BankDepositShare}_{b,s,t-1}$

This table reports the result of the first-stage in the instrument variable regression. As shown in the above equation, I use local bank capital ratios to predict nonbank servicing portfolio market shares. $\text{NonbankServicingMarketShare}_{s,t}$ is the market share of nonbank servicers in state s and quarter t. $\text{BankCapitalRatio}_{s,t}$ is the average local bank capital ratio, which is the weighted average capital ratio of banks in a region, with the weight being each bank branch's deposit share in the region in the previous year. $\text{BankCapitalRatio}_{i,t}$ is the capital ratio of bank i in quarter t, and $\text{BankDepositShare}_{b,s,t-1}$ is the deposit share of branch b (which belongs to bank i) in state s in the previous year. $X_{s,t}$ includes the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, and proportion of first-home buyers in the specific state and quarter. α_s and γ_t are state and quarter fixed effects. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset. Bank capital ratio and deposit share data is from banks' call reports. The sample includes 990 points, covering 20 quarters from 2014 to 2019 and 50 states. All standard errors are clustered by state and quarter.

Table 3.11: **IV Regression Second-Stage**

Dependent Variable:	ComplaintRatio%
Model:	(1)
$\text{Nonbank}\widehat{\text{ServicingMarketShare}}\%$	0.0041**
	(0.0019)
OrigRate	0.0030
	(0.0614)
OrigLoanTerm	-0.0020*
	(0.0011)
OrigLtv	-0.0169***
	(0.0056)
OrigCreditScore	0.0024
	(0.0014)
OrigAvgUpb10k	-0.0084
	(0.0051)
RefiPct	-0.0036**
	(0.0015)
FirstHomePct	0.0035
	(0.0026)
Date	Yes
Region	Yes
Observations	990
R^2	0.79435
Within R^2	0.01305

Clustered (Date & Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

$$\text{ComplaintRatio}_{s,t} = \beta_2\, \text{Nonbank}\widehat{\text{ServicingMarketShare}}_{s,t} + \Gamma X_{s,t} + \alpha_s + \gamma_t + \epsilon_{s,t} \tag{3.8}$$

This table reports the result of the second-stage in the instrument variable regression. As shown in the above equation, I investigate the relation between the predicted nonbank servicing market shares in the first stage and complaint ratios across state s and quarter t. $X_{s,t}$ includes the average origination interest rate, months to maturity, loan-to-value ratio, borrower credit score, loan balance amount, proportion of refinance loans, and proportion of first-home buyers in the specific state and quarter. α_s and γ_t are state and quarter fixed effects. Servicing portfolio data comes from Fannie Mae and Freddie Mac's Loan Performance dataset. Complaint data is from the CFPB Complaint Database. The sample includes 990 points, covering 20 quarters from 2014 to 2019 and 50 states. All standard errors are clustered by state and quarter. The variable of interest is β_2, which measures the difference in complaint ratios in areas with different predicted market shares of nonbank servicers.

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