How Do Lender-Household Relationships Affect Mortgage Refinancing?

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October 2025

Abstract

What role do lenders play in household refinancing? This paper provides insights into this question. Using granular household-level data, the paper shows that an exogenous disruption to lender-household relationships substantially reduces a household's refinancing probability by 43.96%. Importantly, households do not switch to other lenders following a disruption. Instead, their probability of refinancing with new lenders also declines by 35.05%. The relationship disruption does not affect refinance loans' interest rates, fees, or performance. The evidence uncovers an informing role of relationship lenders, in which relationship lenders help households refinance by informing them of potential refinancing opportunities. The paper further develops a dynamic structural model and evaluates counterfactual policies targeted at relationship lenders.

Keywords: Lender-Household Relationships, Mortgage Refinancing, Household Finance, Financial Intermediaries

JEL Classification: D83, G21, G28, G51

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†I am deeply grateful to Ron Kaniel (Chair), Yufeng Huang, Yukun Liu, and Christian C. Opp for invaluable guidance and support. I also thank Taylor Begley, Joao F. Gomes, Narayana Kocherlakota, Alexandr Kopytov, Renping Li, Alan Moreira, Robert Novy-Marx, Alex Priest, Joanna Wu, Billy Xu, Yang Yi, and Pavel Zryumov for helpful comments and suggestions. All errors and omissions are my own.

1 Introduction

Mortgage debt occupies a preeminent place in household balance sheets (Badarinza et al., 2016), and refinancing is an important tool for households to manage this debt. However, households often fail to refinance their mortgages even when substantial savings are available (Keys et al., 2016). A large literature has explored the reasons from the borrower side, including factors such as inattention and suspicion (Andersen et al., 2020, Byrne et al., 2023, Johnson et al., 2019). Yet few studies examine the role lenders play in household refinancing. This paper provides new evidence on this question.

This paper asks how lender-household relationships affect mortgage refinancing. Lender-household relationships refer to relationships established through interactions between lenders and households, which may involve communication and information sharing. The paper investigates the causal effects of lender-household relationships on household refinancing, and develops a dynamic structural model to evaluate counterfactual policies.

I construct a granular household-level dataset by combining Verisk, HMDA, and GSE data. To identify the causal effects, I exploit lender mergers and acquisitions (M&As) as exogenous disruptions to lender-household relationships, conditional on a matched sample. Specifically, the relationship lender is defined as the lender that originated the household's existing mortgage. The treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. Each treated household is matched with control households located in the same county, holding comparable existing mortgages prior to the lender M&A shock, and never having experienced a lender M&A shock.

Lender M&As plausibly disrupt lender-household relationships. They often involve branch closures, renamings, and service disruptions. These changes can disrupt key interactions within the relationships. First, relationship lenders actively inform their customers about market updates and new products, in order to promote business and maintain relationships. However, M&As may disrupt communication channels and undermine information credibility, thereby constraining lenders' ability to inform their customers. During M&As, offline communication can be disrupted by branch closures and loan officer replacements, and online communication can be affected by IT integration. At the same time, brand renamings and service disruptions may erode customers' trust (Arita et al., 2025), making the information provided by lenders less credible. Second, in addition to relationship lenders' informing, M&As may undermine other interactions. One example is the soft information about customer quality. Yet M&A-induced loan officer turnover might result in the loss of the soft information held by those officers (Allen et al., 2016).

Recent cases support that lender M&As can disrupt lender-household relationships (Appendix A4). In 2022, Truist transitioned around seven million SunTrust customers to a new digital system and rebranded 2,000 branches following the M&A. The move was criticized for poorly executed technological migration and inadequate customer support. As a result of the frustrating experience, some customers ended decade-long banking relationships (Kline, 2022). In 2024, the transfer of First Republic customers to JPMorgan Chase following the M&A also drew criticism for service disruptions (Saeedy, 2024).

An identification challenge is that the lending relationship and household refinancing behavior may be confounded by unobservable household characteristics. For example, households with high financial proficiency might be more adept at both managing the lending relationship and making refinancing decisions. Using lender M&As as shocks may mitigate this concern. Lender-level M&As are typically driven by firm-wide strategy, making them plausibly independent of unobservables of individual households.

While lender M&As are plausibly exogenous to the unobservables, they may still correlate with some observables. Therefore, I employ a matching procedure to control for a wide range of other factors that might influence household refinancing other than the relationship disruptions, including sample selection, local economic conditions, and changes in lender-level characteristics. A concern is that the lenders being acquired might differ from an average lender in the market, and therefore their relationship borrowers might differ from an average borrower, raising sample selection issues. While it is possible, matching on pre-shock borrower characteristics possibly makes the treated households, defined as those whose relationship lender was acquired, comparable to the controls. Pre-trend tests support this comparability, showing no significant differences in refinancing behavior between treated and control groups prior to the M&As. I also provide robustness using a sample additionally matched on pre-shock lender characteristics. While lender M&As and local economic conditions might be correlated, for example, when the local area is a major market for the lender, or when M&As influence lenders' market competition[1], matching the sample on county makes the M&As potentially exogenous. Another concern is that M&As might change lender-level characteristics. For example, acquiring and acquired lenders may differ in their refinance contracts or loan approval criteria. Thus, when the treated households face different practices of the acquiring lenders after M&As, they may change refinancing behavior accordingly. To address this concern, I construct an Acquirer-Matched Sample for robustness, in which the control group not only satisfies the aforementioned matching criteria but also consists only of households whose relationship lender is the corresponding acquiring lender. This ensures that treated and control households face the same lender after the M&As, ruling out lender-level drivers.

The results show that the exogenous disruption to lender-household relationships substantially reduces household refinancing probability. Treated households are 43.96% less likely to refinance relative to the sample average. Importantly, households do not switch to other lenders following a disruption. Instead, their probability of refinancing with new lenders also declines by 35.05% relative to the sample average. Further tests show that, conditional on refinance loans, the relationship disruption has no statistically or economically significant effect on the refinance loans' interest rates, fees, or performance.

The evidence is consistent with the informing role of relationship lenders, in which relationship lenders help households refinance by informing them of potential refinancing opportunities (the **relationship-lender-informing channel**). Lenders actively reach out to

[1]Agarwal et al. (2023), Scharfstein and Sunderam (2016), Liebersohn (2024) show that market competition can affect lenders' refinancing product offerings.

their relationship customers about potential refinancing opportunities in order to earn loan origination fees and maintain relationships, real-world examples of which are provided in Appendix A5. The communication from relationship lenders serves as a key information source for borrowers. According to the National Survey of Mortgage Originations, 69% of refinancing borrowers report relying heavily on their mortgage lender or broker to learn about mortgages or mortgage lenders (Appendix A6).

Importantly, the relationship-lender-informing channel is consistent with the finding that households are less likely to refinance with new lenders after the relationship disruptions: after the relationship breaks, households are less likely to be aware of potential refinancing opportunities and therefore less likely to refinance, regardless of whether with relationship lenders or new lenders.

Alternative mechanisms cannot account for the findings. The relationship lending literature has focused on that relationship lenders can collect private information about borrowers, which may generate advantages that are private to the relationship pair, such as better performance (Allen et al., 2016) and lower costs (Buchak et al., 2023). However, those advantages are private to the relationship pair, therefore predicting that households losing access to those advantages should be more likely to switch to the next best refinancing opportunity, implying an increased probability to refinance with new lenders. The empirical evidence contradicts this prediction. Moreover, the channel predicts changes in refinance loans' costs or performance, yet no such changes are observed in the results. A related explanation is soft information sharing across lenders through loan officers' personal connections. I test robustness among lenders less likely to rely on such soft information sharing, including depository institutions without local branches and fintech lenders operating almost entirely online with minimal human involvement. The results show that relationship disruptions still significantly reduce households' switching to these lenders, indicating that soft information sharing cannot explain the findings.

I further explore the relationship-lender-informing channel, including the potential sources of its effectiveness and its cross-sectional heterogeneity. The channel highlights that relationship lenders can effectively inform households about refinancing opportunities. While this paper does not take a stand on the exact sources of the effectiveness, I provide suggestive evidence on two potential sources, including the strong communication ability of relationship lenders, and the high credibility of the information they provide, both of which may mitigate documented frictions that cause households to fail to refinance (Andersen et al., 2020, Byrne et al., 2023, Johnson et al., 2019). I also explore cross-sectional heterogeneity. The relationship-lender-informing channel is more effective when the refinancing interest rate is low. The channel is also more effective when relationship lenders have more local branches, are smaller in size, or operate as mortgage companies or state-chartered banks.

While the reduced-form results are well identified, several important questions remain. First, the combination of refinancing costs and random variation in interest rates makes refinancing a real option problem. Therefore, a structural model that incorporates the dynamic feature is necessary to quantify the household refinancing decision. Second, counterfactual analysis is essential for assessing the potential impact of related policies. Given the importance of refinancing, policies such as the Home Affordable Refinance Program were implemented to influence refinancing activity. The critical role of relationship lenders in facilitating refinancing raises the question of whether policies targeted at relationship lenders could encourage households to refinance. At the same time, customer protection regulations, such as the California Consumer Privacy Act, impose restrictions on business marketing practices. In the mortgage refinancing context, such policies may reduce the relationship lenders' informing ability, thereby generating unintended adverse effects.

Accordingly, I develop a dynamic structural model of lender-household relationships and household refinancing. The model is adapted from the inattention model in Andersen et al. (2020) with two important differences. First, I extend their static structural model to a dynamic setting. This allows me to incorporate the real-option feature of refinancing, thereby quantifying the inattention friction and the importance of the relationship-lender-informing channel. Second, I allow relationship lender characteristics to impact the likelihood that households pay attention to refinancing. This captures the key finding in my paper, that relationship lenders can inform households and impact their attentiveness to refinancing opportunities.

The model is estimated using full-information maximum likelihood estimation. Value functions are computed on a discretized state space with 7.4 million grid points. I further employ the model to evaluate policies targeted at relationship lenders. Regarding potential policies to promote refinancing, a policy that increases relationship lenders' informing ability raises average borrower welfare by 30.65%, measured as the refinancing rate multiplied by the net present value per refinance. This policy is substantially more effective than one that reduces refinancing cost of comparable scale, which raises welfare by 7.53%. This finding is consistent with the literature emphasizing inattention as a key obstacle to household refinancing (Andersen et al., 2020, Byrne et al., 2023). Regarding a policy that restricts relationship lenders' outreach, such a policy reduces average borrower welfare by 26.24%, raising concerns about whether marketing restrictions should be tailored differently in the mortgage refinancing industry.

The paper proceeds as follows. Section 2 describes the data. Section 3 provides causal evidence on how lender-household relationships affect household mortgage refinancing. Section 4 presents a dynamic structural model of relationships and refinancing. Section 5 concludes.

Related Literature

The paper contributes to the literature on households' failure to refinance. Keys et al. (2016) document that households often fail to refinance their mortgages even when substantial savings are available. Andersen et al. (2020) find inattention is one of the reasons why households fail to refinance. Consistent with inattention, Byrne et al. (2023) conduct a field experiment in Ireland in which customers were mailed information about refinancing opportunities, and they find that simply sending a reminder letter can largely increase refinancing probability. Johnson et al. (2019) study why people did not take up favorable refinancing opportunities offered through a policy program, and they find that customer suspicion is the main obstacle. People receiving the offer doubted that the deals were "too good to be true". While the literature focuses on explaining the failure to refinance, this paper contributes by uncovering and quantifying the importance of relationship lenders in mitigating this failure. Specifically, I document that relationship lenders can effectively inform households of potential refinancing opportunities, thereby helping households refinance, and I provide quantification of the importance of this relationship-lender-informing channel.

A related finding in Buchak et al. (2023) is that fintech lenders employ technology to encourage borrowers to refinance, and they utilize this ability to exploit market power, charging higher markups to borrowers. While both papers find that lenders can prompt borrowers to refinance, the scope and mechanism differ. Buchak et al. (2023) focus on fintech lenders, while the conclusions of this paper generally apply to all types of lenders. Buchak et al. (2023) emphasize technology as the mechanism to facilitate borrower refinancing, which fintech lenders leverage to generate market power and charge markups. By contrast, this paper identifies the provision of information, which makes borrowers attentive to refinancing opportunities, improving borrower welfare without price distortion. Lastly, while Buchak et al. (2023) provide correlational evidence regarding fintech lenders' customer acquisition ability, I use exogenous shocks to identify the causal effects of the relationship lenders' information provision.

This paper also relates to the literature on relationship lending. The relationship lending literature focuses on that relationship lenders can collect private information about borrowers over interactions, and examines the implications of utilizing such information in both household and corporate lending. In household financing, Allen et al. (2016) argue that soft information allows banks to more accurately identify safer consumers for lending and to better target borrowers who need counseling, and they show that the destruction of soft information increases consumer bankruptcy rates. Agarwal et al. (2018) find that lenders can use borrower information to mitigate credit risk on credit card accounts. Buchak et al. (2023)

argue that integrated lenders have a cost advantage in refinancing their servicing customers, potentially because they already possess the customers' identity and credit information, and this cost advantage can lower refinancing fees and enhance refinancing probability. In corporate financing, the use of private information about borrowers could benefit borrowers through lower interest rates, a reduced likelihood of pledging collateral (A. N. Berger and Udell, 1995), and increased credit availability (Petersen and Rajan, 1994), and can benefit lenders through a higher probability of selling future loans to their relationship borrowers (Bharath et al., 2007). Potential downsides of lenders' use of private information about borrowers are also discussed, for example, in Rajan (1992).

This paper contributes to the literature along two important dimensions. First, the channels differ. While the literature focuses on a channel in which relationship lenders collect information about borrowers, this paper highlights a channel in which relationship lenders provide information to borrowers. Second, the implications differ. Because the information collected about borrowers is often private to lenders, any potential advantage derived from such information remains private to that relationship pair. In contrast, lenders' provision of information to borrowers may awaken them to explore financing opportunities outside the relationship, implying positive spillovers beyond the relationship.

In addition, this paper contributes to the modeling of household refinancing. Some studies focus on households' refinancing timing. For example, Agarwal et al. (2013) derive a closed-form optimal refinancing rule, and Andersen et al. (2020) develop a model incorporating both household inattention and psychological costs. Among the papers modeling households' choices of lenders, Allen et al. (2019) study search and negotiation in the mortgage market, while D. W. Berger et al. (2024) emphasize refinancing costs. This paper connects two strands of literature, modeling household optimal refinancing timing with endogenous household choice of relationship lenders.

More broadly, this paper connects to studies examining lenders' impacts on refinancing from perspectives other than relationships. Some papers explore how lender competitiveness affects refinancing outcomes (Agarwal et al., 2023, Scharfstein and Sunderam, 2016, Liebersohn, 2024). Others focus on supply-side barriers arising from underwriting constraints (DeFusco and Mondragon, 2020, Beraja et al., 2019).

2 Data

This paper constructs a granular household-level dataset that combines three sources of data: Verisk, HMDA, and GSE. **Verisk** (formerly Infutor) provides property-level mortgage history data. It sources data from public records, including the County Recorder's Office and County Assessor's Office, and supplements with additional mortgage information from multiple sources. Verisk applies a verification process to ensure data accuracy. The data have been used in the literature, for example, Coven (2023) use its mortgage data, and Diamond et al. (2019) use its individual address histories and demographics data. It covers properties from more than 3,000 counties nationwide, tracks an average of 25 years of historical data and ends in the latest year for which property taxes were billed. For each property, it provides details of the three most recent mortgage contracts, including mortgage date, loan amount, loan term, interest rate, lender, and rate type (fixed or adjustable). I exclude contracts that do not represent new originations, such as mortgage modifications. In addition, I collect property information, including unique property ID, census block–level location, and the latest deed transaction date.

I supplement the Verisk data with loan costs, borrower income and loan type from HMDA. Home Mortgage Disclosure Act (**HMDA**) data is a loan-level dataset that covers nearly the entire universe of U.S. mortgage originations and applications. HMDA reports borrower income and loan type throughout the sample period, and includes loan costs starting in 2018. I merge HMDA loan originations from 2003 to 2023 with Verisk loans using exact matching on loan year, loan amount, property's census tract, lender, and, when applicable, loan term. The matching procedures are described in Appendix A1. To ensure accuracy, only one-to-one matches are kept.

Lastly, I supplement the Verisk data with loan performance information, using the Freddie Mac and Fannie Mae Single Family Loan Performance Data (Government-Sponsored Enterprise, **GSE** data). The GSE data provides information on the GSEs' portfolios of fully amortizing, full documentation, single-family, fixed-rate mortgages. The GSE data are first matched with HMDA using a matching approach adapted from in Buchak and Jørring (2021) with modifications. Specifically, I merge GSE and HMDA loans through exact matching on loan year, zip code, loan amount, loan purpose, occupancy type, construction method, purchaser type, lender, and, when applicable, loan term, interest rate, total units, and prepayment penalty. The matching procedures are described in Appendix A1. To ensure accuracy, only one-to-one matches are kept. The matched GSE data are then linked to Verisk through the Verisk–HMDA matches.

I classify a new loan origination as a refinance if its amount is between 70% and 130% of the remaining balance of the previous unmatured mortgage on the same property of the same owner, or if it can be matched with a refinance loan in HMDA. The amount-based classification reflects the idea that a refinance loan typically pays off the outstanding balance of the previous loan and is therefore similar in size.[2] The Verisk–HMDA matched sample allows me to validate the accuracy of the amount-based classification. HMDA provides a refinance loan flag, defined as "a closed-end mortgage loan or an open-end line of credit in which a new, dwelling-secured debt obligation satisfies and replaces an existing, dwelling-secured debt obligation by the same borrower".[3] Conditional on being identified as a refinance by the amount-based classification, 90.43% of loans are also flagged as refinance in HMDA, indicating reasonable validity. Besides, as a robustness check, I replicate main empirical analyses using only the Verisk–HMDA matched loans and HMDA's refinance flags, and the results are robust.

[2] In the literature without a direct refinance indicator (Gerardi et al., 2023), an alternative approach is to proxy it by prepayments of borrowers whose address does not subsequently change.

[3] https://www.consumerfinance.gov/rules-policy/regulations/1003/2/

I apply the following filters to construct the main sample. I restrict the data to mortgages originated between 2003 and 2023. To ensure that each property is associated with a single household, I exclude mortgages dated prior to the property's most recent deed transaction. This removes loans originated by previous property owners and allows each property to be treated as a single household starting from its latest ownership transfer. I further limit the sample to households that have ever held a 30-year mortgage, which constitute the majority of loans in the U.S. mortgage market. I also restrict the sample to households whose first mortgage originated in 2014 or earlier, ensuring at least ten years of observation to study refinancing behavior.[4] Summary statistics of the sample are reported in Table 1. Panel A presents loan-level statistics: the average mortgage amount is $210,988 , with a term of 28 years and an interest rate of 4.41%. I construct a household–year panel for the main analysis, reported in panel B, in which the annual refinancing probability is 5.46%.

Appendix A2 evaluates the sample representativeness. I compare loans in the Verisk-HMDA matched sample (prior to applying sample filters) with the full HMDA dataset, and the patterns are consistent. In addition, I validate the Verisk interest rate data by regressing the HMDA loan interest rate on the Verisk loan interest rate using matched loans from 2018 onward. The coefficient is 1.04, with an R^2 of 96.06%. Using only fixed-rate loans yields a coefficient of 1.02 and an R^2 of 97.42%.

Lender M&As data are obtained from the National Information Center (NIC). The NIC data covers select banks and institutions for which the Federal Reserve has a supervisory, regulatory, or research interest. It covers banks, mortgage companies, credit unions, and other institutions. The M&A data includes the acquisition dates and the identities of the acquiring and acquired lenders. The data uses RSSD IDs as lender identifiers and are matched with the loan sample in two steps. First, using the Verisk–HMDA matched sample, I construct links between Verisk lender–year–county pairs and HMDA lender IDs, which are then connected to RSSD IDs through the HMDA Panel. Second, I apply these trained

[4]The results are not sensitive to this sample restriction, including all households regardless of their observation length does not alter the conclusions.

matches to map all Verisk lenders to RSSD IDs. For cases without a direct match at the lender–year–county level, I further attempt to link at the lender–year–state level using a similar procedure. In total, 765 acquired lenders are matched with loan-level data. I restrict the M&As sample to events where the acquired lenders ceased operating as independent entities. To ensure that M&As are exogenous, I exclude acquired lenders that experienced failure or were subject to enforcement actions by the Office of the Comptroller of the Currency (OCC) during the merger year or the preceding year. Data on failures are obtained from NIC, and enforcement actions are obtained from OCC.

Additional lender characteristics are drawn from several sources. Lender type is obtained from NIC. Using HMDA, I calculate three measures: the lender's market share in the mortgage market, the share of the lender's originations that are refinance loans, and the share of the lender's originations that were not sold by the time of reporting. For depository institutions, I supplement these with data on total assets and the number of branches from the Summary of Deposits.

3 Empirical Evidence

This section provides causal evidence on how lender-household relationships affect household mortgage refinancing. The first part discusses the effects on refinancing probability. The second part examines, conditional on refinance loans, the effects on the refinance loan performance. The third part discusses the effects on the refinance loan interest rate and costs. The fourth part explores the underlying channels. Lastly, I discuss extensions.

3.1 Refinancing Probability

3.1.1 Identification

To identify causal effects, I use lender M&As as exogenous disruptions to lender-household relationships, conditional on a household-level matched sample.

The relationship lender is defined as the originator of the existing mortgage. In the case of M&As, I assume that acquiring lenders inherit the borrower relationships of the acquired lenders following the acquisitions. Appendix A3 illustrates that this definition of relationship lenders remains applicable when servicing rights are sold to other entities or when borrowers originated loans with multiple lenders.

The treated households are those whose relationship lender was acquired, with the M&A effective year designated as event year zero. Each treated household's sample spans from the year the relationship was established to the latest year available.[5] Following the literature, I restrict the treated households to those with 30-year fixed-rate loans prior to the shocks, which constitute the majority of loans in the U.S. mortgage market. Each treated household is matched with control households located in the same county, holding comparable existing mortgages prior to the lender M&A shock, but never experienced a lender M&A shock. The control households are selected through a two-step procedure: First, households that never experienced a lender M&A are exactly matched with treated households based on the year, property county, and the term of the existing mortgage in event year –1. Second, among these exact matches, I apply propensity score matching based on the amount, interest rate, dummies for mortgage age of the existing mortgage in event year –1, as well as refinance history during event years (-4,-1). The five nearest neighbors are selected as controls. This sample enables me to compare refinancing behavior of the treated households with those of the control households located in the same county and holding comparable existing loans. In the main analysis, I examine the matched households' refinancing probability over a four-year window centered on the event year.

Lender M&As plausibly disrupt lender-household relationships. They often involve branch closures, renamings, and service disruptions. Table A1 summarizes branch changes after the M&As for lenders that are covered by the SOD and involved in M&As that are matched with the loan-level data. One year after being acquired, 43% of acquired lenders' branches

[5]Households experiencing multiple lender M&As are dropped.

were closed and 54% were renamed. News reports indicate customer dissatisfaction with M&A-induced service disruptions. These changes can disrupt key interactions within the relationships. First, relationship lenders actively inform their customers about market updates and new products, in order to promote business and maintain relationships. However, M&As may disrupt communication channels and undermine information credibility, thereby constraining lenders' ability to inform their customers. During M&As, offline communication can be disrupted by branch closures and loan officer replacements, and online communication can be affected by IT integration. At the same time, brand renamings and service disruptions may erode customers' trust (Arita et al., 2025), making the information provided by lenders less credible. Second, in addition to relationship lenders' informing, M&As may undermine other interactions. One example is the soft information about customer quality. Yet M&A-induced loan officer turnover might result in the loss of the soft information held by those officers (Allen et al., 2016).

Recent cases support that lender M&As can disrupt lender-household relationships (Appendix A4). For example, in 2022, Truist transitioned around seven million merged SunTrust customers to a new digital system and rebranded 2,000 branches. The move was criticized for poorly executed technological migration and inadequate customer support. Kline (2022) report that customers experienced difficulties using mobile and online banking, faced prolonged waiting time to reach representatives, and failed to obtain solutions from branch managers. An angry customer decided to end a 38-year banking relationship with SunTrust due to the frustrating experience. In the month following the integration, the number of complaints filed against Truist with the Consumer Financial Protection Bureau (CFPB) increased by more than 81% relative to that in the month preceding the integration. Another example is the 2024 transfer of First Republic customers to JPMorgan Chase following the M&A, in which customers complained about the service disruptions and terrible communication (Saeedy, 2024).

An identification challenge is that the lending relationship and household refinancing behavior may be confounded by unobservable household characteristics. For example, households with high financial proficiency might be more adept at both managing the lending relationship and making refinancing decisions. Using lender M&As as shocks may mitigate this concern. Lender-level M&As are typically driven by firm-wide strategy, making them plausibly independent of unobservables of individual households.

While lender M&As are plausibly exogenous to the unobservables, they may still correlate with some observables. Therefore, I employ a matching procedure to control for a wide range of other factors that might influence household refinancing other than the relationship disruptions, including sample selection, local economic conditions, and changes in lender-level characteristics. A potential concern is that the lenders being acquired might differ from an average lender in the market, and therefore their relationship borrowers might differ from an average borrower, raising sample selection issues. To address this, I firstly exclude acquired lenders in abnormal conditions, as indicated by failures or enforcement actions. Further matching on pre-shock borrower characteristics possibly makes the treated households, defined as those whose relationship lender was acquired, comparable to the controls. Pre-trend tests support this comparability, showing no significant differences in refinancing behavior between treated and control groups prior to the M&As. I also provide robustness using a sample additionally matched on pre-shock lender characteristics. Lender M&As and local economic conditions might be correlated. For example, the local area might be a major market for the lender. Another example is that M&As may impact lenders' market competition, and Agarwal et al. (2023), Scharfstein and Sunderam (2016), Liebersohn (2024) show that market competition can affect lenders' refinancing product offerings. The sample matched on county compares treated and control households exposed to the same local economic conditions and competitive environment, making the M&As plausibly exogenous. Another concern is that M&As might change lender-level characteristics. For example, acquiring and acquired lenders may differ in their refinance contracts or loan approval criteria. Thus, when the treated households face different practices of the acquiring lenders after M&As, they may change refinancing behavior accordingly. To address this concern, I construct an Acquirer-Matched Sample for robustness, in which the control group not only satisfies the aforementioned matching criteria but also consists only of households whose relationship lender is the corresponding acquiring lender. This ensures that treated and control households face the same lender after the M&As, ruling out lender-level drivers.

3.1.2 Results

Using the matched sample, I estimate specification 1. The dependent variable $Refi_{i,t}$ takes one if household i refinances in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(Event\ Year\ \delta)_t$. The regression includes household by matched group fixed effects τ_i and event year fixed effects γ_δ. The coefficient β_δ captures the difference in refinancing probability between the treated households and the control households in event year δ, relative to their difference in event year -1.

$$Refi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(Event\ Year\ \delta)_t + \tau_i + \gamma_\delta \tag{1}$$

Figure 1 plots the coefficients of estimating 1, highlighting several takeaways. First, there are no significant differences between the treated and control groups prior to the shock, supporting the exogeneity of the lender M&As. Second, the disruption of lender-household relationships generates a strong negative effect on household refinancing probability. Households that experienced a disruption in their lender relationship were less likely to refinance. Lastly, the effect persists in several years since the shock, and shows a reversal afterwards. This suggests that rebuilding the lender-household relationship may take time.

To examine the average effect in the post-event period, I estimate specification 2. The independent variable is an interaction term between the indicator for treated households

$\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$.

$$Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(Post)_t + \tau_i + \gamma_\delta \tag{2}$$

Table 2 column (1) reports the results. On average, the treated household's overall refinancing probability decreases by 0.0196. Column (2) additionally controls for the existing mortgage's amount, interest rate, age, and term, and the decrease is 0.0240. Compared to the average refinancing rate of 0.0546 in the full sample, this represents a 43.96% decline.

An important question is whether the large decline in refinancing probability stems from the loss of relationship lenders or from a failure to switch to new lenders. To investigate this, I decompose the overall refinancing probability into two components: refinancing with the relationship lender and refinancing with new lenders. The dependent variable in column (3) and (4) takes one if household i refinances with relationship lenders in year t. In column (3), the treated household's probability of refinancing with the relationship lender decreases by 0.0100. With controls in column (4), the decrease is 0.0124, corresponding to a 57.67% decline compared to the average refinancing rate with relationship lenders in the full sample. Column (5) and (6) examine refinancing with new lenders. The dependent variable takes one if household i refinances with new lenders in year t. In Column (5), the treated household's probability of refinancing with new lenders decreases by 0.0096. With controls in column (6), the decrease is 0.0116, corresponding to a 35.05% decline relative to the average refinancing rate with new lenders in the full sample. The results show that the disruption of lender-household relationships not only reduces the overall refinancing probability. Importantly, households do not switch to other lenders following a disruption. Instead, their probability of refinancing with new lenders also declines.

Robustness

I firstly address the concern that M&As might change lender-level characteristics, for example, the acquiring lenders may offer less favorable contracts post M&As, thereby changing household refinancing probability, rather than due to disruptions in lender-household relationships. First, this explanation is inconsistent with the results. If the acquiring lenders offer less favorable loan contracts after the M&As, borrowers should be more likely to switch to new lenders to refinance. Instead, the decline in refinancing with new lenders contradicts this prediction. Second, as a robustness check, I re-estimate specifications 1 and 2 using the Acquirer-Matched Sample, in which the control group not only satisfies the aforementioned matching criteria, but also consists only of households whose relationship lender is the corresponding acquiring lender. The results are reported in Appendix A7.1. The overall refinancing probability decreases by 0.0181, and the probability to refinance with a new lender decreases by 0.0072, confirming the robustness of the main findings. The coefficients are smaller in magnitude than those in Table 2. It is expected, because treated and control households are matched on both location and lender, the design effectively restricts the sample to cases where acquirers were already present in the targets' local markets. A well-established local presence likely enables acquirers to maintain and re-establish borrower relationships more effectively after the acquisitions.

Secondly, I address the concern about the misclassification of refinance loans. I re-estimate the specifications using only the Verisk-HMDA matched loans, which allows me to replace my classification with HMDA's refinance flag. This sample also enables additional controls for loan type and borrower income. I further restrict the sample to households holding conventional loans prior to the shock and include borrower income in the propensity score matching. I also include loan type and borrower income of the existing loan in the regression controls. Results, reported in Appendix A7.2, show that the overall refinancing probability decreases by 42% relative to the sample mean, and the probability of refinancing with new lenders decreases by 48% relative to the sample mean, confirming the robustness of the main findings.

Third, a potential concern is that acquired lenders may differ systematically from other lenders, raising sample selection issues for treated households. This does not appear to be the case, as there is no evidence of differential pre-trends in refinancing behavior between treated and control households in Figure 1. As an additional robustness check, I control for relationship lender characteristics in both the propensity score matching and the regression specifications in Appendix A7.3. The lender characteristics include the market share in mortgage originations, the share of refinance loans among its mortgage originations, and the share of mortgages that remained unsold at the time of reporting. Results remain robust. This robustness test, with controls for lender-level characteristics, also helps to rule out concerns that the results are driven by lender characteristics changes.

3.2 Refinance Loan Performance

This section examines whether the refinance loan performance of the treated and control households differs using the household-level matched sample. The dependent variable $\textit{Loan Delinquent}_{i,t}$ takes one if the household i's refinance loan was ever 90 or more days delinquent on payments in year t. The variable is defined conditional on a refinance loan. Figure 2 plots the coefficients from the estimation of specification 1. Table 3 reports the coefficients from the estimation of specification 2. The differences between the treated and control loan performance are statistically insignificant. The results show that the treated households' refinance loans exhibit similar performance to the those of control households, and suggest that the disruption of lender-household relationships does not significantly affect the borrower quality.

Robustness

Besides examining the performance of refinance loans, I also examine the performance of all loans, including both refinance and non-refinance loans. This allows me to assess borrower quality without conditioning on the decision to refinance. The results, reported in Appendix A8, confirm no significant differences in borrower quality.

3.3 Refinance Loan Costs

This section studies, conditional on the refinance loans, if shocks on lender-household relationships affect the refinance loan interest rate and costs.

3.3.1 Identification

Similarly, I use lender M&As as exogenous disruptions to lender-household relationships, conditional on a loan-level matched sample.

Specifically, treated loans are the fixed-rate refinance loans of households whose relationship lender was acquired, with the M&A year designated as event year zero. Each treated loan is matched with control loans, which are comparable refinance loans of households located in the same county, holding comparable loans before refinancing, but were never affected by a lender M&A shock. The control loans are selected through a two-step procedure. First, refinance loans of households that never experienced a lender M&A are exactly matched with treated loans based on the year, property county, and the term of the treated loan. Second, among these exact matches, I apply propensity score matching based on the loan amount of the refinance loans, and the amount, interest rate, term and age of the previous loans. The five nearest neighbors are selected as controls. It is important to control for observables about the previous loans in this setting, because one of the primary motivations for refinancing is to reduce the existing interest rate.

3.3.2 Results

Using the matched sample, I estimate specification 3. The dependent variable Y_f represents the characteristics of refinance loan f, including interest rate and total loan costs. The independent variables are interaction terms between an indicator for treated loans $\mathbf{1}(Treated)_f$ and indicators for event year $\mathbf{1}(t = \delta)_t$. I control for matched group fixed effects κ_g, event year fixed effects γ_δ, and the treatment status $\mathbf{1}(Treated)_f$.[6] The coefficient β_δ captures the difference in outcomes between the refinance loans of treated households and the refinance loans of control households in event year t, relative to their difference in event year -1.

$$Y_f = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_f \times \mathbf{1}(Event\ Year\ \delta)_t + \mathbf{1}(Treated)_f + \kappa_g + \gamma_\delta \tag{3}$$

To examine the average effect in the post-event period, I estimate specification 4, in which the independent variable is an interaction term between the indicator for treated loans $\mathbf{1}(Treated)_f$ and an indicator for the post-event period $\mathbf{1}(Post)_t$.

$$Y_f = \alpha + \beta \mathbf{1}(Treated)_f \times \mathbf{1}(Post)_t + \mathbf{1}(Treated)_f + \kappa_g + \gamma_\delta \tag{4}$$

Taking the interest rate as the dependent variable, Figure 3(a) plots the coefficients from the estimation of specification 3. There are no significant differences between the treated and control groups prior to the lender M&As, supporting the exogeneity of the shock. At the same time, the two groups also show no significant differences after the M&As. Table 4 column (1) and (2) reports the corresponding average effect, it is -0.0024% when controlling the loan amount of the refinance loans, and the amount, interest rate, term and age of the previous loans. It is statistically insignificant and economically small. Similarly, taking total loan costs as the dependent variable, Figure 3(b) and Table 4 column (3) and (4) show that the differences between the treated and control loans remain statistically insignificant and economically small.

The results suggest that lender-household relationships have no impact on refinancing costs, either in interest rates or total loan costs. The relationship lender does not gain

[6] Most households refinance only once in the sample, so it is infeasible to control for household fixed effects.

market power to charge a markup, potentially reflecting the highly standardized interest rate setting and a competitive environment in U.S. mortgage market (D. W. Berger et al., 2024).

3.4 Channels

The results demonstrate that lender-household relationships help households refinance in improving refinancing probability, without impacts on refinancing costs or refinance loan performance. This section discusses the channel through which relationship lenders help household mortgage refinancing.

Relationship-Lender-Informing channel Relationship lenders can inform borrowers of potential refinancing opportunities and draw their attention to them.[7] Lenders actively reach out to their relationship customers about potential refinancing opportunities. Appendix A5 presents a real email and news examples in which relationship lenders inform borrowers about potential refinancing opportunities. Lenders are motivated to earn loan origination fees and maintain relationships. As reported in Table 1, lenders earn an average of $4,155 in origination fees, which is about 2% of the loan amount. Meanwhile, lenders' potential losses from borrowers' refinancing are limited. According to HMDA data from 2003 to 2023, lenders sold 70% of originated loans to other entities, such as GSEs, within the origination year. Because lenders do not hold the majority of loans themselves, they are largely insulated from losses in mortgage payments when borrowers refinance to lower interest rates.

Survey evidence support the important informing role of relationship lenders. The National Survey of Mortgage Originations (NSMO), managed by the Federal Housing Finance Agency (FHFA) and the CFPB, surveys a nationally representative sample of newly originated closed-end first-lien residential mortgages. From the first quarter of 2014 to the second

[7] The relationship-lender-informing channel discussed here is broadly similar to the one studied in bank advertising. In the retail banking sector, Honka et al. (2017) and Mendes (2024) show that bank advertising primarily functions by providing information about potential options, rather than by persuading customers to make a purchase.

quarter of 2022, the NSMO surveyed 25,214 borrowers whose mortgages were to refinance or modify an earlier mortgage. Among these borrowers, 69% reported their mortgage lender or broker as their primary source to get information about mortgages or mortgage lenders, over three times the frequency of the second most common source, websites (20%). The responses highlight that relationship lenders serve as a primary and dominant information source for refinancing borrowers. Among refinancing borrowers who rely on their lender or broker for information, 46% considered more than one lender for refinancing. It suggests that, after receiving refinancing information, borrowers will consider refinancing opportunities broadly, including those with their relationship lenders as well as with new lenders. The survey details are described in Appendix A6.

Importantly, the relationship-lender-informing channel is consistent with the finding that households are less likely to refinance with new lenders after the relationship disruptions: after the relationship breaks, households are less likely to be aware of potential refinancing opportunities and therefore less likely to refinance, regardless of whether with relationship lenders or new lenders.

Alternative mechanisms cannot account for the observed patterns. The relationship lending literature has focused on that relationship lenders can collect private information about borrowers, which may generate advantages that are private to the relationship pair. Relationship lenders might possess soft information about borrower quality (Allen et al., 2016), which enables relationship lenders to help borrowers face illiquidity and improve loan performance. Buchak et al. (2023) argue that integrated lenders have a cost advantage in refinancing their servicing customers, potentially because they already possess the customers' identity and credit information, and this advantage can lower refinancing fees and enhance refinancing probability. However, those advantages are private to the relationship pair, therefore predicting that households losing access to those advantages should be more likely to switch to the next best refinancing opportunity, implying an increased probability to refinance with new lenders. The empirical evidence rejects this prediction. Moreover, the channel predicts changes in refinance loans' costs or performance, yet no such changes are observed in the results.

A subsample test by borrower income fails to support either the cost advantage channel or the soft information channel. The cost advantage channel, if present, predicts that relationship disruptions should have more negative effects on households that are more sensitive to costs. Similarly, the soft information channel predicts more negative effects for households that rely more on soft information. Low-income households, relative to high-income households, are generally more vulnerable to refinancing costs and more reliant on soft information. Therefore, both mechanisms predict that low-income households should experience a stronger effect. Table A6 splits the sample into high- and low-income groups based on the treated households' most recent reported income prior to the shock, within the same state and income-reporting year. The results show no significant differences between the two groups, providing no support for either the cost advantage channel or the soft information channel.

Another possible mechanism is soft information sharing across lenders through loan officers' personal connections. For example, loan officers of different institutions may use their personal connections to share referrals that facilitate households' switching to new lenders. When relationships are disrupted, such cross-lender referrals disappear, making households less likely to refinance with new lenders. I test robustness of households' switching to new lenders that rely less on such referrals. The first group of lenders are depository institutions without local branches. Depository institutions such as banks typically rely on local staff and personal interactions to originate loans. For those not located in the county of the property, their staff are less likely to be embedded in local soft information networks. Therefore, borrowers' probability to refinance with such nonlocal depositories should not be affected by soft information sharing across lenders. Table 5 column (1) (2) present the tests. The dependent variable takes one if a household refinances with new lenders that are nonlocal depositories. The refinancing probability decreases by 0.0011, which corresponds to 23% of the full sample mean of refinancing with new lenders that are nonlocal depositories. The second group of lenders are fintech lenders. I use the list from Buchak et al. (2018) to identify fintech lenders, which defines fintech lenders as those where nearly the entire mortgage application process occurs online with minimal human involvement. Therefore, refinancing is unlikely to be driven by soft information sharing across lenders. Table 5 column (3) (4) reports the results, in which the dependent variable takes one if a household refinances with new lenders that are fintech lenders. The refinancing probability decreases by 0.0010, which represents 48% decline relative to the full sample mean of refinancing with new lenders that are fintech lenders. Taken together, after relationship disruptions, households are less likely to switch to new lenders with limited reliance on soft information sharing, confirming that the soft information sharing across lenders does not drive the results.

Overall, the results are consistent with the relationship-lender-informing channel. Alternative mechanisms cannot account for the observed patterns.

3.5 Extensions

This section further explores the relationship-lender-informing channel, including the potential sources of its effectiveness and its cross-sectional heterogeneity.

Potential Sources of the Effectiveness

The results indicate that relationship lenders can effectively inform households about refinancing opportunities. While this paper does not take a stand on the exact sources of the effectiveness, this section explores two possibilities.

The effectiveness of the relationship-lender-informing channel potentially stems from the strong communication ability of relationship lenders, and the high credibility of the information they provide, both of which may mitigate documented frictions that cause households to fail to refinance. Andersen et al. (2020) find inattention is one of the reasons why households fail to react to low interest rates. Consistent with inattention, Byrne et al. (2023) conduct a field experiment and find that sending a reminder letter to households can largely improve their refinancing probability. The strong communication ability of relationship lenders, such as the high frequency with which they provide information, may mitigate the documented inattention frictions. Furthermore, customers are cautious about refinancing opportunities. Johnson et al. (2019) document that suspicion is the main obstacle to households taking up favorable refinancing opportunities. Relationship lenders are more likely to be trusted by borrowers, implying a high credibility of the information they provide, which may mitigate the mistrust frictions.

I exploit variation in the post-M&A branch changes. Following M&As, closed branches experience location closures and full turnovers of loan officers. In contrast, branches that are alive and renamed remain operational and may experience only partial turnover of loan officers. Therefore, branch closures may represent a larger disruption to relationship lenders' communication ability than branch renamings, and the difference in outcomes between these two scenarios may offer suggestive evidence for the importance of relationship lenders' communication ability. Table 6 splits the sample based on the target lenders' post-M&A local branch changes. The target lenders refer to the treated households' relationship lenders, which, by construction, are the lenders being acquired. Column (1) reports results using the subsample in which over 50% of the target lender's branches in the county as of event year -1 are closed within four years post-M&A. Column (2) reports results using the subsample in which over 50% of the target lender's branches in the county as of event year -1 remain operational but are renamed within four years post-M&A.

The results suggest two patterns. First, households whose relationship lenders' local branches are mostly closed after being acquired experience a larger decline in refinancing probability, compared with households whose relationship lenders' local branches are mostly renamed. The difference is 0.0104 and is significant at the 5% level, which represents 19% of the average refinancing rate in the full sample. This suggests the potential importance of lenders' communication ability for the effectiveness of the relationship-lender-informing channel. Second, households whose relationship lenders' local branches are mostly renamed after being acquired also experience a substantial decline in refinancing probability. The decrease is 0.0190 and is significant at the 1% level, which represents 35% of the average refinancing rate in the full sample. This suggests the main results are not fully driven by M&A-induced branch closures. M&As can also hurt the relationship-lender-informing channel for branches that remain operational, plausibly suggesting a deterioration in information credibility. Overall, the results provide suggestive evidence that both communication ability and information credibility are potential sources of the effectiveness of the relationship-lender-informing channel.

Cross-Sectional Heterogeneity

This section explores cross-sectional heterogeneity of the strength of the relationship-lender-informing channel, including the refinancing interest rate and the relationship lender characteristics.

The relationship-lender-informing channel implies that its strength should vary with the refinancing interest rate. Specifically, when the refinancing interest rate is high, refinancing is less likely to provide rate reductions. Therefore, after households get informed of refinancing opportunities, they are less likely to take action. In other words, in high interest rate periods, the relationship-lender-informing channel should become less effective in improving refinancing probability, predicting that M&A-induced declines in refinancing probability would be smaller when the interest rate is high. Table 7 examines this prediction. In column (1), the independent variables add the market mortgage interest rate in the current year and its interaction with $Treat \times Post$.[8] In column (2), the independent variables add the one-year change in the market mortgage interest rate, defined as the difference between the rate in the current year and the rate in the previous year, and its interaction with $Treat \times Post$.

First, the coefficients on the interest rate and on the one-year change in the interest rate are negative, implying that households are less likely to refinance when faced with high interest rates. This is consistent with the fact that one of the main motivations for

[8]The market mortgage interest rate is collected from the Freddie Mac Primary Mortgage Market Survey (PMMS) series, specifically the 30-Year Fixed Rate Mortgage Average in the United States.

refinancing is to lower interest rates, and since this objective becomes less likely when interest rates are high, households are less likely to refinance. Second, the interaction terms have positive coefficients, suggesting that when the interest rate is high, M&A-induced declines in refinancing probability are smaller, consistent with the relationship-lender-informing channel. Particularly, column (1) shows that when the interest rate is one standard deviation higher, the M&A-induced change in refinancing probability increases by 0.0014, which represents 2.52% of the average refinancing rate in the full sample. The coefficient is significant at the 1% level. The coefficient of the interaction term in column (2), though insignificant, is also positive with a similar magnitude. When the one-year change in the interest rate is one standard deviation higher, the M&A-induced change in refinancing probability increases by 0.0008, which represents 1.40% of the average refinancing rate in the full sample.

The strength of the relationship-lender-informing channel may vary with relationship lender characteristics, including the number of branches, size, and type. Lenders with more local branches may have stronger informing and relationship-maintenance capacity. This implies that relationship borrowers of acquired lenders with greater local branch presence should experience larger declines in refinancing probability after the shocks. Table 8 column (1) tests this prediction using matched households whose treated lenders are depository institutions, with branch data from the SOD. the independent variables add an interaction term between $Treat \times Post$ and the target lender's number of branches per 100,000 population in the county in event year -1.[9] Consistent with the prediction, when acquired lenders' branch share is one standard deviation higher, an M&A leads to a 24% larger decline in refinancing probability compared with that of lenders without local branches. This suggests that borrowers of branch-intensive lenders rely more on the relationship-lender-informing channel.

Smaller lenders, such as community banks that focus more on local markets, may be

[9]The population data is collected from the Census Bureau. The target lender's number of branches is not additionally controlled because, being measured in event year -1, it is time-invariant and thus absorbed by the household by matched group fixed effects.

better at informing borrowers. This implies that relationship borrowers of smaller acquired lenders experience larger declines in refinancing probability after the shocks. Table 8 column (2) test this prediction using matched households whose treated lenders are depository institutions, with total assets data from the SOD. the independent variables add an crossing term between $Treat \times Post$ and the target lender's share of total assets among all U.S. depository institutions, in units of percentages, in event year -1. Consistent with the prediction, when acquired lenders' asset share is one standard deviation higher, an M&A leads to a 12% smaller decline in refinancing probability compared with that of lenders of negligible size. This suggests that borrowers of smaller lenders rely more on informing channel.

Finally, lenders of different types vary in their communication approaches. For example, large banks often rely on local branch networks, whereas mortgage companies might outperform in online marketing. Lenders are grouped into the following categories based on the NIC classification: National Bank (NAT), Domestic Entity Other(DEO, including mortgage companies such as Rocket Mortgage, LLC), State Chartered Bank (SCB, including State Member Banks and Non-member Banks), and all other lenders. Table 8 Column (3) reports the results. The reduction in refinancing probability is robust across all lender types, while borrowers in relationships with mortgage companies and state-chartered banks experience larger declines than those with national banks.

4 A Structural Model of Lender-Household Relationships and Refinancing

The empirical evidence shows that relationship lenders help households refinance by informing them of potential refinancing opportunities. While the results are well identified, several important but underexplored questions remain. First, the combination of refinancing costs and random variation in interest rates makes refinancing a real option problem. Therefore, a structural model that incorporates the dynamic feature is necessary to quantify the household refinancing decision. Second, counterfactual analysis is essential for assessing the potential impact of related policies. Given its importance, policies were implemented to influence refinancing activity. For example, Home Affordable Refinance Program (HARP) relaxed housing equity constraints by extending government credit guarantee on insufficiently collateralized refinanced mortgages (Agarwal et al., 2023). The critical role of lenders in facilitating refinancing raises the question of whether lender-targeted policies could encourage households to refinance. Meanwhile, there are policies restricting business marketing for customer protection. For example, the Federal Communications Commission restricts telemarketing to customers, even those with existing relationships, and the California Consumer Privacy Act limits businesses' personalized marketing when customers opt out. In the mortgage refinancing, such policies may reduce the ability of relationship lenders to inform borrowers about refinancing opportunities, thereby generating unintended adverse effects.

Motivated by these considerations, I develop a dynamic structural model of how lender-household relationships affect household refinancing. The model is adapted from the inattention model in Andersen et al. (2020) with two important differences. First, I extend their static structural model to a dynamic setting. This allows me to incorporate the real-option feature of refinancing, thereby quantifying the inattention friction and the importance of the relationship-lender-informing channel. Second, I allow relationship lender characteristics to impact the likelihood that households pay attention to refinancing. This captures the key finding in my paper, that relationship lenders can inform households and impact their attentiveness to refinancing opportunities.

The first part presents the model. The second part describes the identification and estimation. The third part discusses the estimation results. The last part conducts counterfactual analyses of potential policy designs.

4.1 Model

I model the household's optimal refinancing decision. Market conditions and the initial mortgage contracts are assumed to be exogenous. Lender characteristics are also assumed to be exogenous, as the empirical evidence suggests no markups generated from the relationships, which is also a common simplifying assumption in the literature estimating individual-level demand (Seiler, 2013).

Timeline

Assume households hold finite-period mortgage contracts. In each period t, household i is characterized by the beginning-of-period remaining term $T_{i,t}$, loan balance $l_{i,t}$, existing interest rate $r_{i,t}$, facing a new refinancing interest rate $R_{i,t}$, and relationship-lender characteristics $RL_{i,t}$. Each period, a household might enter one of two states: "normal" or "other-motive-refinancing".

The "normal" state captures household inattention and refinancing behavior in normal times, following the framework of Andersen et al. (2020). Specifically, conditional on being in the normal state, a household is "asleep" with probability w_{it}, being inattentive to refinancing opportunities, thus does not refinance. With probability $1 - w_{it}$, a household is "awake", being aware of potential refinancing opportunities, thus choose which lender to refinance with, or choose not to refinance. One key feature of the model is that relationship lender characteristics RL_{it} can impact the probability of being asleep w_{it}, as modeled in equation 5. This captures the key finding in the paper, that relationship lenders can inform households and impact their attentiveness to refinancing opportunities. To proxy for the strength of the relationship lenders' informing ability, motivated by the reduced-form evidence, RL_{it} includes the relationship lender type $rltype_{i,t}$ (depository or non-depository), and for depository institutions, its size $rlsize_{i,t}$ and number of local branches $rlnbr_{i,t}$.[10] The relationship lender is the originator of the existing mortgage by the end of the previous period. Thus, for household i entering period t, RL_{it} is fixed, and any decision to switch lenders affects RL

[10] Size and branch data are only available for depository institutions.

only from the next period $t+1$ onward. This ensures that the relationship-related variables reflect characteristics observed before households receive information.

$$w(RL_{it}) = \frac{\exp(\chi' RL_{it})}{1+\exp(\chi' RL_{it})}$$
$$\chi' RL_{it} = 1(rltype_{it} = Deps.) * (\chi_1 + \chi_2 * rlsize_{i,t} + \chi_3 * rlnbr_{i,t}) + \chi_4 * 1(rltype_{it} = NonDeps.) \tag{5}$$

Besides of "normal" state, household may enter "other-motive-refinancing" state. This state captures refinancing motivated by factors other than lowering interest rates, such as extracting equity for liquidity management purposes (Chen et al., 2020) or shortening loan maturity. It is not uncommon that household refinance to extra equity even at cost of higher rate. For example, Freddie Mac reports that in the first half of 2023 the average rate on new refinance loans was 2.2% higher than the rate on the loans being refinanced (FreddieMac, 2023). The "other-motive-refinancing" state capture such behaviors: households refinance regardless of interest rate. In this state, the household will refinance with one lender, i.e., there is no outside option not to refinance. As this motivation is not the focus of the paper, I assume that households enter this state exogenously with probability p_e. The assumption is in line with Zhang (2024), who model refinancing for moving and cash-out purposes through an exogenous probability. Formally, p_e is specified as follows, in which ρ is the parameter to be estimated.

$$p_e = \frac{1}{1+exp(\rho)} \tag{6}$$

Choice-Specific Flow Utility

Following simplifying assumptions in modeling individual refinancing behavior (Andersen et al., 2020, Fisher et al., 2024), I assume that a household refinances from a fixed-rate mortgage to another fixed-rate mortgage, without changing the loan term or principal amount. I also assume that, for refinancing, each household's consideration set consists of the relationship lender and one non-relationship lender.

An awake household can choose which lender to refinance with, or choose not to refinance. The choice-specific flow utility is described as follows.

If the household choose not to refinance, the household gets a flow utility $\widetilde{v}_{d=0,it}$ in equation 7. $m(l,r,t)$ is the per-period mortgage payment for a mortgage with loan balance l, interest rate r, and remaining term t, following the amortization of the loan, $m(l,r,t) = l \cdot \frac{r(1+r)^t}{(1+r)^t-1}$. The scalar parameter μ governs the household's responsiveness to the mortgage payments. ϵ is an unobserved shock, and the deterministic component is denoted by $v_{d=0,it}$. Thus, for a household choose not to refinance, the flow utility is the scaled negative mortgage payments plus a random shock.

$$\widetilde{v}_{d=0,it} = \mu * [-m(l_{i,t}, r_{i,t}, T_{i,t})] + \epsilon_{d=0,it} \equiv v_{d=0,it} + \epsilon_{d=0,it} \tag{7}$$

If the household refinance with a new lender, the household gets a flow utility $\widetilde{v}_{d=new,it}$ in equation 8. In this case, the mortgage payment $m()$ switches from the old rate r_{it} to the new rate R_{it}, at a refinancing cost ζ_{it}. The baseline refinancing cost ζ_{it} is calibrated as 1% of mortgage amount plus $2,000 (Agarwal et al., 2013). ϵ is a unobserved shock, and the deterministic component is denoted by $v_{d=new,it}$.

$$\widetilde{v}_{d=new,it} = \mu * [-m(l_{it}, R_{it}, T_{it}) - \zeta_{it}] + \epsilon_{d=new,it} \equiv v_{d=new,it} + \epsilon_{d=new,it} \tag{8}$$

If the household refinance with the relationship lenders, the household gets $\widetilde{v}_{d=rl,it}$ in equation 9. In this case, the mortgage payment $m()$ switches from the old rate r_{it} to the new rate R_{it}, with a baseline refinancing cost ζ_{it} plus an additional loyalty advantage κ_{it}. The loyalty advantage κ_{it} captures the advantages that are private to the relationship pair, and therefore influence the household's decision of which lender to choose. For example, a positive value of κ_{it} implies that refinancing with the relationship lender incurs higher utility, relative to non-relationship lenders. This may reflect cost-relevant factors such as lower refinancing fees, soft-information-induced services to improvement loan performance, or a behavioral preference for familiar institutions. κ_{it} is a function of relationship lender characteristics $RL_{i,t}$. By construction, $\kappa(RL_{it})$ is expressed in the same units as monetary payments, allowing the utility impact of loyalty advantage to be interpreted in equivalent dollar terms. ϵ is a unobserved shock, and the deterministic component is denoted by $v_{d=rl,it}$.

$$\begin{aligned}\widetilde{v}_{d=rl,it} &= \mu * [-m(l_{it}, R_{it}, T_{it}) - \zeta_{it} + \kappa(RL_{it})] + \epsilon_{d=rl,it} \equiv v_{d=rl,it} + \epsilon_{d=rl,it} \\ \kappa(RL_{it}) &= 1(rltype_{it} = Deps.) * (\phi_1 + \phi_2 * rlsize_{i,t} + \phi_3 * rlnbr_{i,t}) + \phi_4 * 1(rltype_{it} = NonDeps.)\end{aligned} \tag{9}$$

An asleep household can not refinance, the household gets a flow utility $v_{d=0,it}$.

A household in other-motive-refinancing will choose one lender to refinance with. The choice-specific flow utility is written equation 10. If the household refinances with a new lender, the household gets $\hat{v}_{d=new,it}$, which equals $v_{d=new,it}$ in equation 8 plus a unobserved shock $\eta_{d=new,it}$. If the household refinances with the relationship lender, the household gets $\hat{v}_{d=rl,it}$, which equals $v_{d=rl,it}$ in equation 9 plus a unobserved shock $\eta_{d=rl,it}$.

$$\begin{aligned}\hat{v}_{d=new,it} &= v_{d=new,it} + \eta_{d=new,it} \\ \hat{v}_{d=rl,it} &= v_{d=rl,it} + \eta_{d=rl,it}\end{aligned} \tag{10}$$

I adopt the conditional independence assumption (Rust, 1987), and also assume the unobservable shocks $\epsilon_{d=new,it}, \epsilon_{d=rl,it}, \epsilon_{d=0,it}, \eta_{d=new,it}, \eta_{d=rl,it}$ are independent and identically distributed (i.i.d.) type I extreme value distribution.

The Dynamic Optimal Refinancing

I first describe the state transitions. The state variables are $S = \{T_{it}, l_{it}, r_{it}, R_{it}; ltype_{it}, lsize_{it}, lbr_{it}; ltype^n_{it}, lsize^n_{it}, lbr^n_{it}\}$. The loan characteristics include the beginning-of-period remaining term T_{it}, the outstanding loan balance l_{it}, the existing interest rate r_{it}, a new refinancing interest rate R_{it}. The relationship-lender characteristics $RL_{it} = [rltype_{it}, lsize_{it}, lbr_{it}]$, including the relationship lender type $rltype_{it}$ (depository or non-depository), and for depository institutions, its size $rlsize_{it}$ and number of local branches $rlnbr_{it}$. The new lender characteristics $RL^n_{it} = [lsize^n_{it}, lsize^n_{it}, lbr^n_{it}]$ are defined analogously. The loan balance l_{it}, the existing interest rate r_{it}, and the relationship lender characteristics RL_{it} evolve endogenously with the household's refinancing decision d_{it}, as given in equation 11, where $d_{it} = 0$ denotes no refinancing, $d_{it} = new$ denotes refinancing with new lenders, and $d_{it} = rl$ denotes refinancing with the relationship lender. The last equation shows that when a household refinances with a new lender, the next-period relationship-lender characteristics are updated accordingly, where k indexes the k-th component of the relationship-lender vector RL.

$$\begin{aligned}
T_{it+1} &= T_{it} - 1 \\
l_{it+1} &= [l_{it}(1 + r_{it}) - m(l_{it}, r_{it}, T_{it})]^{1(d_{it}=0)} * [l_{it}(1 + R_{it}) - m(l_{it}, R_{it}, T_{it})]^{1(d_{it}=new)+1(d_{it}=rl)} \\
r_{it+1} &= r_{it}^{1(d_{it}=0)} * R_{it}^{1(d_{it}=new)+1(d_{it}=rl)} \\
RL_{k,it+1} &= RL_{k,it}{}^{1(d_{it}=0)+1(d_{it}=rl)} * RL^n_{k,it}{}^{1(d_{it}=new)}
\end{aligned} \tag{11}$$

The new refinancing interest rate R_{it}, and the new lender characteristics RL^n_{it} are exogenous. The rate R_{t+1} is modeled as the current rate R_t plus an i.i.d. normally distributed shock, which with mean zero and a standard deviation calibrated using the annualized standard deviation of the Freddie Mac 30-year mortgage rate from April 1971 to December 2023. I assume lender-side characteristics evolve slowly. Therefore, the next-period new lender characteristics remain same as their current levels.

Consider a household with state variable S and making decision d (suppressing subscripts $_{i,t}$). The choice-specific value functions are denoted by $\widetilde{V}_{d,S}$ and $\hat{V}_{d,S}$. $\widetilde{V}_{d,S}$ refers to the value function when making choice d in state S under the normal state. $\hat{V}_{d,S}$ refers to the value function when making choice d in state S under the other-motive-refinancing state. They are solved in the equations 12, in which β is the discount rate, calibrated as 0.95, EV is the expected value at the beginning of the next period as a function of next-period states S', and the deterministic components are denoted by $V_{d,S}$. As a function of EV, the deterministic components of choice-specific value functions $V_{d,S}$ have closed-form expressions.

In the normal state:

$$\widetilde{V}_{d=new,S}=\widetilde{v}_{d=new,it}+\beta*EV(S'|S,d=new)=v_{d=new,it}+\beta*EV(S'|S,d=new)+\epsilon_{d=new,it}\equiv V_{d=new,S}+\epsilon_{d=new,it}$$

$$\widetilde{V}_{d=rl,S}=\widetilde{v}_{d=rl,it}+\beta*EV(S'|S,d=rl)=v_{d=rl,it}+\beta*EV(S'|S,d=rl)+\epsilon_{d=rl,it}\equiv V_{d=rl,S}+\epsilon_{d=rl,it}$$

$$\widetilde{V}_{d=0,S}=\widetilde{v}_{d=0,it}+\beta*EV(S'|S,d=0)=v_{d=0,it}+\beta*EV(S'|S,d=0)+\epsilon_{d=0,it}\equiv V_{d=0,S}+\epsilon_{d=0,it}$$

In the other-motive-refinancing state:

$$\hat{V}_{d=new,S}=\hat{v}_{d=new,it}+\beta*EV(S'|S,d=new)=v_{d=new,it}+\beta*EV(S'|S,d=new)+\eta_{d=new,it}\equiv V_{d=new,S}+\eta_{d=new,it}$$

$$\hat{V}_{d=rl,S}=\hat{v}_{d=rl,it}+\beta*EV(S'|S,d=rl)=v_{d=rl,it}+\beta*EV(S'|S,d=rl)+\eta_{d=rl,it}\equiv V_{d=rl,S}+\eta_{d=rl,it} \tag{12}$$

The expected value functions EV can be written in equation 13, in which γ is Euler's gamma. EV will be solved numerically.

$$
\begin{aligned}
EV(S'|S,d) =& E_{S'|S,d}\Big\{p_e * E_{\eta'}(max(\hat{V}_{d=new,S'}, \hat{V}_{d=rl,S'})) \\
&+ (1-p_e) * (1-w(S')) * E_{\epsilon'}(max(\widetilde{V}_{d=new,S'}, \widetilde{V}_{d=rl,S'}, \widetilde{V}_{d=0,S'})) \\
&+ (1-p_e) * w(S') * V_{d=0,S'}\Big\} \\
=& E_{S'|S,d}\Big\{p_e * (log(e^{V_{d=new,S'}} + e^{V_{d=rl,S'}}) + \gamma) \\
&+ (1-p_e) * (1-w(S')) * (log(e^{V_{d=new,S'}} + e^{V_{d=rl,S'}} + e^{V_{d=0,S'}}) + \gamma) \\
&+ (1-p_e) * w(S') * V_{d=0,S'}\Big\}
\end{aligned}
\tag{13}
$$

The value functions are solved by backward induction. In the final period of the mortgage contract, in which the beginning-of-period remaining term T equals one, the mortgage is fully repaid and no further payments occur. Hence, the expected value at the beginning of the next period $EV(S'|S, T = 1, d)$ equals zero.

The likelihood function of each observation can be expressed in value functions in equations 14 . Denote the household-year level outcomes from data by y_{itNEW} and y_{itRL}, in which y_{itNEW} takes one if household i refinances with new lenders at time t, and y_{itRL} takes one if household i refinances with the relationship lender at time t. The log-likelihood function for the full sample is given in equation 15.

$$
\begin{aligned}
P_{new,S_{it}} &= p_e * \frac{e^{V_{d=new,S}}}{e^{V_{d=new,S}} + e^{V_{d=rl,S}}} + (1-p_e)*(1-w(S))*\frac{e^{V_{d=new,S}}}{e^{V_{d=new,S}} + e^{V_{d=rl,S}} + e^{V_{d=0,S}}} \\
P_{rl,S_{it}} &= p_e * \frac{e^{V_{d=rl,S}}}{e^{V_{d=new,S}} + e^{V_{d=rl,S}}} + (1-p_e)*(1-w(S))*\frac{e^{V_{d=rl,S}}}{e^{V_{d=new,S}} + e^{V_{d=rl,S}} + e^{V_{d=0,S}}} \\
P_{0,S_{it}} &= (1-p_e)*(w(S) + (1-w(S))*\frac{e^{V_{d=0,S}}}{e^{V_{d=new,S}} + e^{V_{d=rl,S}} + e^{V_{d=0,S}}})
\end{aligned}
$$

$$
L_{it} = P_{0,S_{it}}^{1-y_{itRL}-y_{itNEW}} * P_{rl,S_{it}}^{y_{itRL}} * P_{new,S_{it}}^{y_{itNEW}} \tag{14}
$$

$$
lnL = \sum_t \sum_i ln(L_{it}) \tag{15}
$$

4.2 Identification and Estimation

Identification

The parameters to be estimated include the vector χ and ϕ, the scalars ρ and μ. χ in equation 5 captures how the lender-household relationship affects the household's probability of becoming inattentive and thus not considering refinancing. ϕ in equation 9 captures the loyalty advantage, reflecting the idea that relationship lenders provide additional utilities to households and thereby influence their lender choice. ρ models the likelihood of entering the other-motive-refinancing state. μ captures the household's sensitivity to the refinancing incentive.

Given a set of lender characteristics, the parameters are identified as follows. χ is identified from the refinancing probability of households facing highly positive incentives to refinance. ϕ is identified from the differences in refinancing incentive when refinancing with the relationship lender and with new lenders occurs with equal probability. μ is identified from the slope of the refinancing probability with respect to refinancing incentive. ρ is identified from the refinancing probability of households facing highly negative incentives to refinance.

Estimation

I apply filters to the household–year panel to construct the structural estimation sample. I keep observations after the households' first 30-year mortgage, and exclude households with loan terms exceeding 30 years, loan amounts below \$10,000 or above \$800,000.[11] These cases are relatively rare, and excluding them reduces computational burden while ensuring that the remaining observations represent the main contracts in the market. Households whose relationship lenders were acquired are excluded to keep the state space computationally manageable. I restrict the sample to households with complete mortgage histories, i.e., with no missing years in the middle. This ensures that I can simulate a full path in the counterfactual analysis. Lastly, 5% of households are randomly sampled.

The new refinancing interest rate $R_{i,t}$ is predicted using the remaining principal, remaining term, county-by-year fixed effects, and a refinancing indicator (which equals one in the prediction sample) as predictors. The prediction model is trained on the full loan-level sample. Relationship-related variables are measured in year $t-1$, ensuring they reflect characteristics observed before households receive information. Specifically, the relationship lender is defined as the originator of the existing mortgage at the end of year $t-1$. It is considered as a depositary lender if it is covered by the SOD, and its size is measured as the share of total assets among all U.S. depository institutions in year $t-1$, in units of percentages, and its branch presence is measured as the number of branches per 100,000 population in the county in year $t-1$. New lender is a representative lender in local market. Its type is proxied by the type of institution originating the largest number of mortgages in the county in year $t-1$, its size is the average asset share of depository institutions operating branches in the county in year $t-1$, and its branch presence is measured as the average number of branches per 100,000 population across depository institutions operating branches in the county in year $t-1$. Mortgage payments and baseline refinancing costs are expressed in thousands of dollars.

[11] The main sample covers households whose first mortgage originated in 2014 or earlier. In 2014, the conforming loan limits were \$417,000 for an one-unit and \$801,950 for a four-unit family. Therefore, the upper bound reasonably cover most conforming loans.

The parameters are estimated using full-information maximum likelihood estimation. Value functions are computed by backward induction on a discretized state space with 7.4 million grid points. In the integration, the expected values EV are derived with numerical simulation, and the choice-specific value functions are then written with the expected values EV.

4.3 Estimation Results

Table 9 presents the estimation results. Panel A reports the estimated parameters, and Panel B reports the effects implied by these parameters. Panel B column (1) summarizes the awake probability $1 - w$. The baseline awake probability for a household whose relationship lender is a depository institution, as implied by the constant term only, is 6.40%. The awake probability increases with the branch presence of depository lenders. Specifically, the average marginal effect (AME) of branch presence, defined as the average partial derivative of the awake probability with respect to branch presence across all observations, is 0.0039. A one standard deviation increase in branch presence results in an 11.02% increase in the awake probability relative to the baseline case. The awake probability decreases with the size of depository lenders. The average marginal effect of lender size is -0.0015, and a one standard deviation increase in lender size leads to an 11.19% decrease in the awake probability relative to the baseline case. For households whose relationship lender is a non-depository lenders, the awake probability is 6.39%.

Column (2) reports the loyalty advantage κ. For households whose relationship lender is a depository institution, Panel A shows that the constant term is statistically insignificant, indicating that refinancing with the relationship lender provides no loyalty advantage relative to refinancing with new lenders. The parameter on branch presence of depository lenders is also statistically insignificant, implying no significant correlation between branch presence and the loyalty advantage. The depository lenders of larger size are associated with higher loyalty advantage, and a one standard deviation increase in lender size leads to \$950 loyalty advantage in monetary equivalent terms. In contrast, non-depository relationship lender impose loyalty disadvantage relative to new lenders, with the disadvantage amounting to \$1,322 in monetary equivalent terms. Column (3) shows that household utility responds positively to monetary incentives, in which lower payments translate into higher utility. Column (4) shows that the probability of entering the other-motive-refinancing state is 3.04%.

In summary, the lender-household relationships substantially affect the likelihood of households becoming attentive to refinancing opportunities. Relationships with depository lenders that have more branches and smaller size increase the probability that households become attentive, consistent with the reduced-form evidence.

4.4 Counterfactual Policy Designs

Policies Promoting Refinancing

Refinancing plays a central role in household debt management and the transmission of monetary policy. Given its importance, policies such as the Home Affordable Refinance Program were introduced to stimulate refinancing activity. The critical role of lenders in facilitating refinancing raises the question of whether lender-targeted policies could encourage households to refinance. This section simulates the effects of two policies targeted at relationship lenders and aimed at promoting household refinancing, using exogenous state variables calibrated to historical data. To make the policies comparable, one policy is modeled as an increase in household attention, while the other is modeled as a reduction in refinancing cost of similar magnitude.

The first policy focuses on increasing attention. Specifically, it raises all relationship lenders' informing ability, therefore all households' awake probability. Examples in practice include the adoption of improved communication technologies or the expansion of branch networks. Figure 4 (a) plots the results. The left graph shows the refinancing rate and the refinancing NPV per refinance. The refinancing NPV is defined as the net present value of mortgage payment savings from the interest rate change, net of refinancing costs, and including the loyalty advantage when refinancing with the relationship lender. The right graph shows the aggregated results, where average social welfare is defined as the refinancing rate multiplied by the refinancing NPV per refinance, reflecting both the refinancing frequency and the gains per refinance. The horizontal axis represents a gradual increase in awake probability. The leftmost point corresponds to the baseline simulated results with estimated parameters (i.e., without policy interventions). In this case, the awake probability is 6.43%, the average net refinancing cost with the relationship lender (defined by the baseline refinancing cost minus the loyal advantage, $\zeta_{it} - \kappa_{it}$) across all observations, is \$4,336, the refinancing rate is 5.28%, the refinancing NPV is \$17,606, and the average welfare is \$930. As the awake probability increases, the refinancing rate rises rapidly, which is unsurprising as more people wake up and the sample covers low-interest-rate periods. The refinancing NPV per refinance decreases, as more frequent refinancing reduces the mortgage interest rates households pay, thereby decreasing the rate reductions from subsequent refinances. The average welfare increases, driven by the higher refinancing rate. At the point the awake probability increases by 58.48%, the refinancing rate is 7.48%, the refinancing NPV is \$16,244, and the average welfare increases from \$930 to \$1,215, representing a 30.65% increase relative to the case without policy intervention.

The second policy targets reducing refinancing cost. Specifically, it improves the loyalty advantage, therefore reducing the net refinancing cost when refinancing with relationship lenders. Examples in practice include reducing up-front costs for loyal borrowers. Figure 4 (b) plots the results. As the net refinancing cost lowers, the refinancing rate, the refinancing NPV per refinance, and average welfare all increase. However, the welfare gains are more modest compared to the "improve wake-up" policy. At the point the net refinancing cost decreases by 57.84%, the refinancing rate is 5.45%, the refinancing NPV is \$18,358, and the average welfare increases from \$930 to \$1000, representing a 7.53% increase relative to the case without policy intervention.

On average, a policy that increases relationship lenders' informing ability is more effective at raising refinancing rates and borrower welfare than a policy that reduces refinancing cost of comparable scale. This is consistent with literature emphasizing inattention as a key obstacle to household refinancing (Andersen et al., 2020) and with evidence showing that simple reminders can substantially increase refinancing activity (Byrne et al., 2023).

Policies Limiting Lenders' Reaching out

As concerns about customer privacy and protection grow, policies have been implemented to restrict business marketing practices. For example, the Federal Communications Commission restricts telemarketing, including to customers with existing relationships, and the California Consumer Privacy Act limits personalized marketing when customers opt out. However, in the mortgage refinancing context, such policies may limit relationship lenders' ability to inform borrowers about refinancing opportunities, potentially leading to unintended adverse effects.

This section explores the impacts of such policies on household refinancing. Consider a "Limit Reaching-Out" policy under which all households become more inattentive. Figure 5 plots the results. The horizontal axis represents a gradual decrease in awake probability, under which the refinancing rate falls rapidly, the refinancing NPV per refinance rises slightly, and average welfare declines sharply. At the point the awake probability decreases by 37.79%, the refinancing rate is 3.78%, the refinancing NPV per refinance is $18,135, and the average welfare is $686, representing a 26.24% decreases relative to the case without policy intervention. This substantial reduction raises important questions about whether marketing restrictions should be tailored differently in the mortgage refinancing sector.

5 Conclusion

This paper studies how lender–household relationships shape refinancing behavior. Exploiting exogenous disruptions from lender M&As, I show that refinancing activity declines sharply when relationships are disrupted, and importantly, households do not switch to new lenders. Instead, their probability of refinancing with new lenders also largely declines. These findings support the relationship-lender-informing channel, in which relationship lenders provide timely and trusted information that facilitates borrower refinancing. Conditional on refinance loans, the disruption does not significantly affect the interest rate, fees, or loan performance, ruling out alternative mechanisms such as cost advantages or soft information.

Building on these findings, I build a dynamic structural model adapted from Andersen et al. (2020), extending their static structural model to a dynamic setting, and allowing relationship lender characteristics to impact the likelihood that households pay attention to refinancing. The estimates reveal that relationships with depository lenders of greater branch presence and smaller size enhance households' awareness of refinancing opportunities. Further counterfactual analysis provides insights for policy design. A policy that enhances households' attention to refinancing opportunities delivers larger welfare gains than a policy of comparable scale that reduces refinancing cost, underscoring inattention as the main barrier for household refinancing. The results suggest that policies improving borrower awareness, such as developing better communication technologies or expanding outreach, can effectively encourage refinancing, with relationship lenders playing an important role in this process. At the same time, policies that restrict relationship lender outreach should be designed with caution to avoid weakening their informing role.

Overall, this paper contributes to both the literature and policy discussions. While the literature on households' failure to refinance focuses on exploring the reasons, this paper highlights the importance of relationship lenders in mitigating this failure. The paper also contributes to the literature on relationship lending, identifying and quantifying the informing role of relationship lenders. Finally, the counterfactual analysis provides insights for policy design, particularly regarding interventions that could leverage the lender-household relationships to impact household refinancing.

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Figures

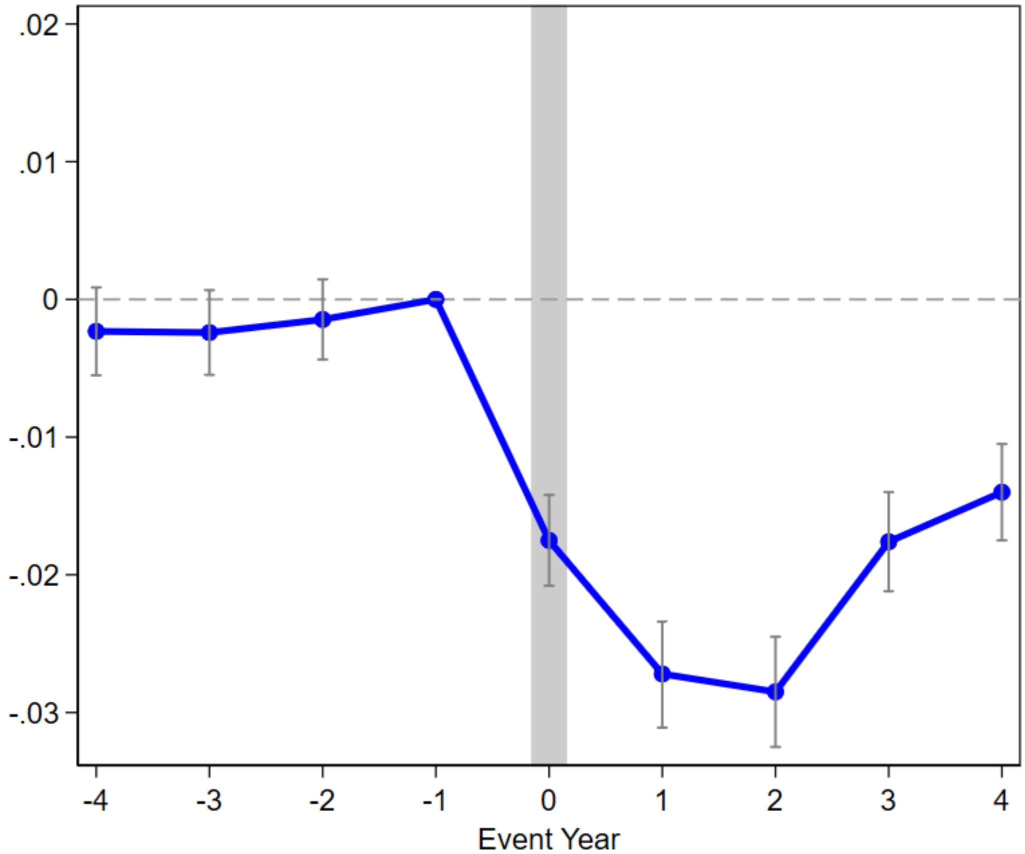


Figure 1: Mortgage Refinancing Probability

Note: This Figure plots the coefficients of $Refi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable $Refi_{i,t}$ takes one if household i refinances in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t = \delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.

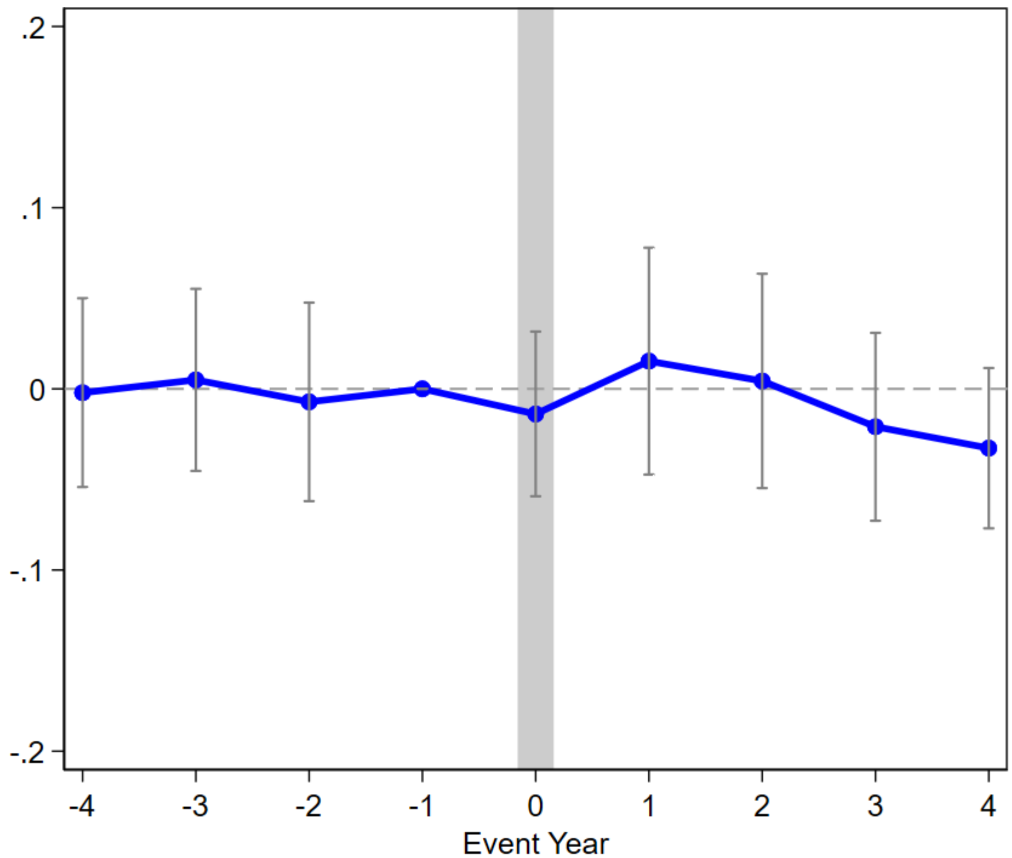
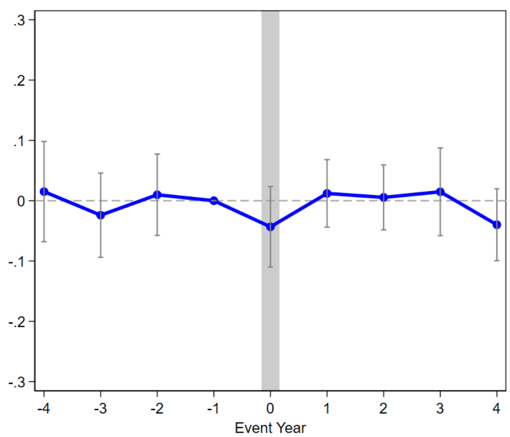
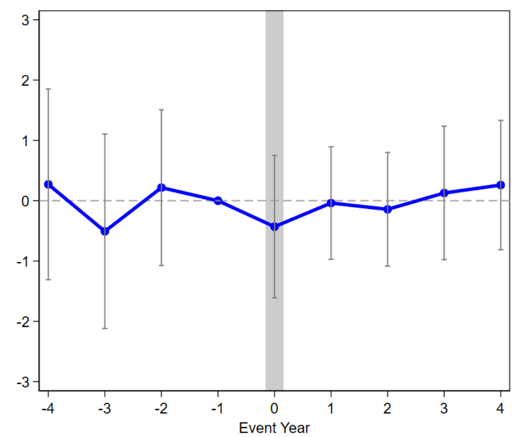


Figure 2: Refinance Loan Performance

Note: This Figure plots the coefficients of $Loan\ Delinquent_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable takes one if the household i's refinance loan was ever 90 or more days delinquent on monthly payments in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t = \delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.



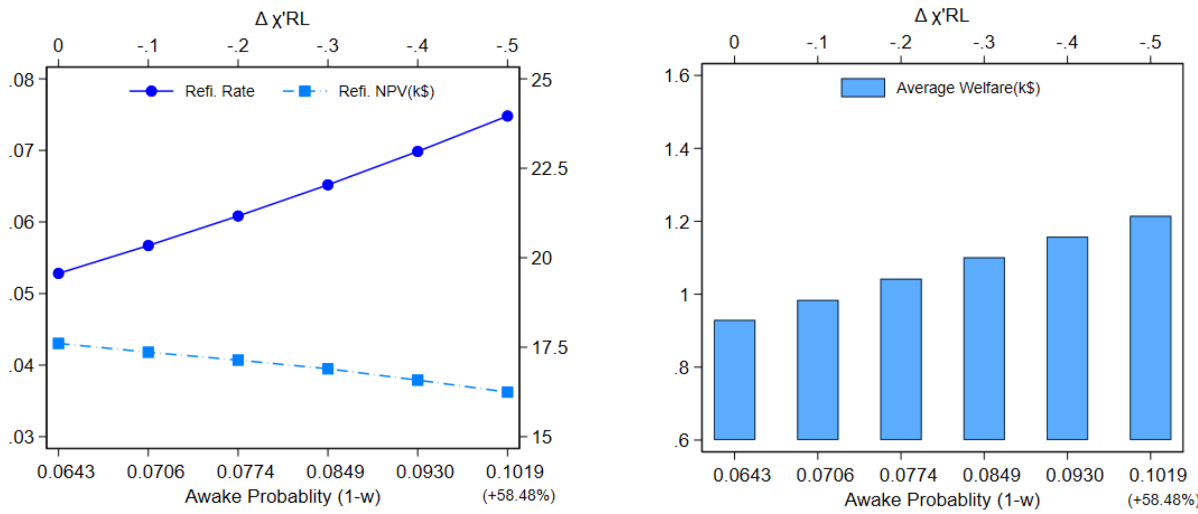
(a) Loan Interest Rate(%)



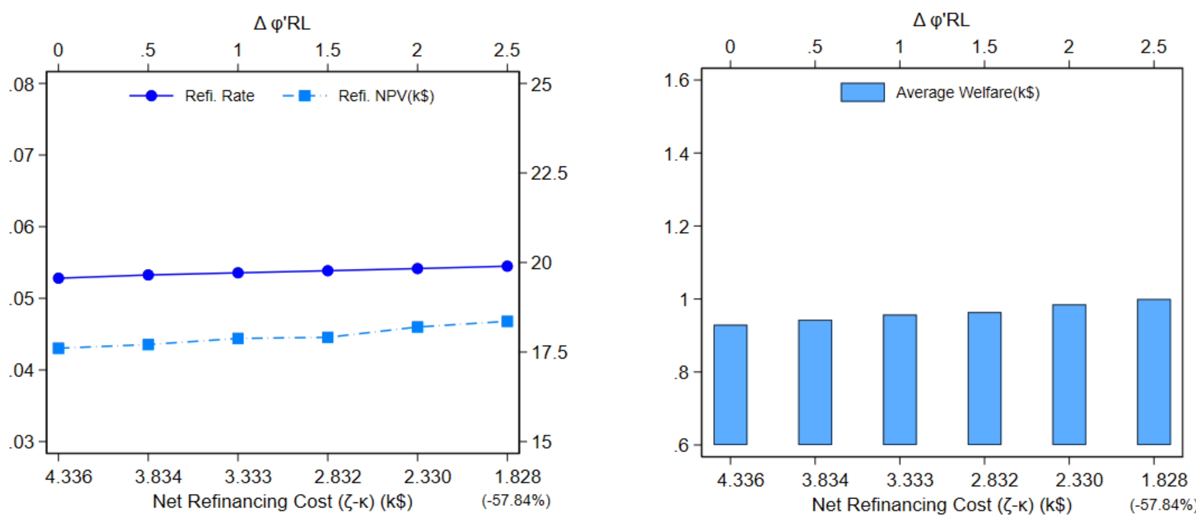
(b) Total Loan Costs(k)

Figure 3: Refinance Loan Interest Rate and Costs

Note: This Figure plots the coefficients of $Y_f = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_f \times \mathbf{1}(t = \delta)_t + \mathbf{1}(Treated)_f + \kappa_g + \gamma_\delta$ using a matched sample. The dependent variable Y_f is the characteristics of refinance loan f, including interest rate and total loan costs. The independent variables are interaction terms between an indicator for treated loans $\mathbf{1}(Treated)_f$ and indicators for event year $\mathbf{1}(t = \delta)_t$. The regression controls matched groups fixed effect, event year fixed effects, and the treatment status. Treated loans are refinance loans of households whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated loan is matched to control loans, which are comparable refinance loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a lender M&A shock.



(a) Policy: Improve Wake-Up



(b) Policy: Reduce Refinancing Cost

Figure 4: Policies Promoting Refinancing

Note: This Figure plots the counterfactual analysis of two policies. The "Improve Wake-Up" policy raises the relationship lenders' informing ability, thus improving households' awake probability. The "Reduce Refinancing Cost" policy reduces refinancing cost by improving the loyalty advantage. The left graph shows the refinancing rate and the refinancing NPV per refinance. The refinancing NPV is defined as the net present value of mortgage payment savings from the interest rate change, net of refinancing costs. The right graph shows the aggregated results, where average social welfare is defined as the refinancing rate multiplied by the refinancing NPV per refinance.

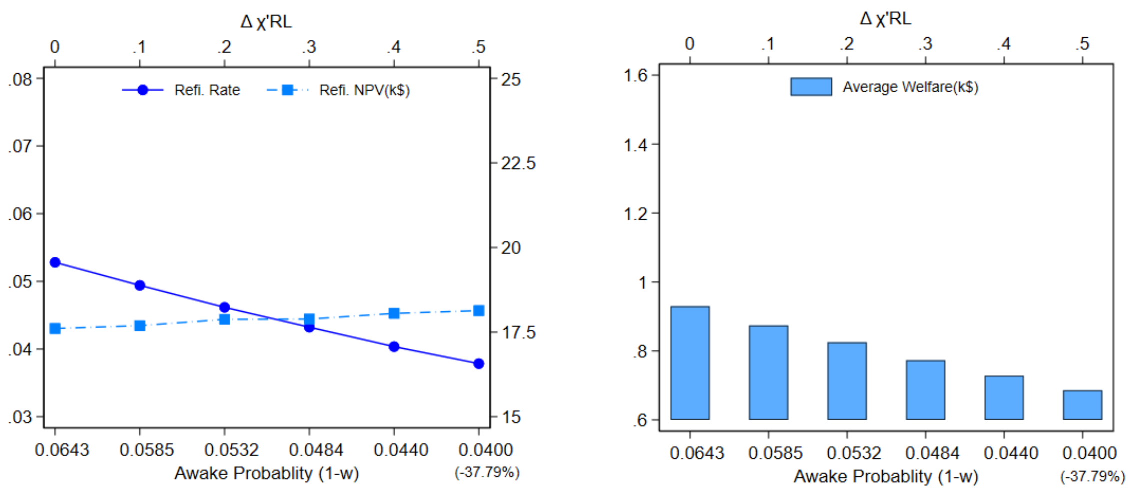


Figure 5: A Policy Limiting Lenders' Reaching out

Note: This Figure plots the counterfactual analysis of a "Limit Reaching-Out" policy that reduces the relationship lenders' informing ability, thus lowering households' awake probability. The left graph shows the refinancing rate and the refinancing NPV per refinance. The refinancing NPV is defined as the net present value of mortgage payment savings from the interest rate change, net of refinancing costs. The right graph shows the aggregated results, where average social welfare is defined as the refinancing rate multiplied by the refinancing NPV per refinance.

Table 1: Summary Statistics

This table describes the summary statistics of the main sample. Panel A presents loan-level statistics. Panel B presents household–year level statistics.

Panel A: Loan Observations				
	Mean	Median	SD	N
Loan Amount(k)	210.9879	173.2090	156.8893	6,505,992
Loan Term(yrs)	27.7983	30.0000	5.6112	6,278,412
Interest Rate(%)	4.4122	4.1250	1.4520	4,102,624
Borrower Income(k)	101.2373	82.0000	71.6862	3,346,140
Total Loan Costs(k)	4.1550	3.3885	3.2418	332,056
Panel B: Household-Year Observations				
	Mean	Median	SD	N
Refi	0.0546	0.0000	0.2272	41,830,397
Refi w. Rel. Lender	0.0215	0.0000	0.1451	41,830,397
Refi w. New Lender	0.0331	0.0000	0.1788	41,830,397
Loan Delinquent	0.0178	0.0000	0.1323	1,076,562

Table 2: Mortgage Refinancing Probability

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable in column (1) (2) takes one if household i refinances in year t, the dependent variable in column (3) (4) takes one if household i refinances with the relationship lender in year t, the dependent variable in column (5) (6) takes one if household i refinances with a new lender in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi		Refi w. Rel. Lender		Refi w. New Lender	
Treated × Post	-0.0196***	-0.0240***	-0.0100***	-0.0124***	-0.0096***	-0.0116***
	(0.0009)	(0.0010)	(0.0006)	(0.0006)	(0.0007)	(0.0008)
Controls		YES		YES		YES
Household FE	YES	YES	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES	YES	YES
Observations	603098	603098	603098	603098	603098	603098
R^2	0.123	0.153	0.126	0.139	0.125	0.144

Table 3: Refinance Loan Performance

This table reports the coefficients of $Loan\ Delinquent_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable takes one if the household i's refinance loan was ever 90 or more days delinquent on monthly payments in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Loan Delinquent	
Treated × Post	-0.0063	-0.0066
	(0.0190)	(0.0204)
Controls		YES
Household FE	YES	YES
Event Year FE	YES	YES
Observations	3984	3984
R^2	0.474	0.477

Table 4: Refinance Loan Interest Rate and Costs

This table reports the coefficients of $Y_f = \alpha + \beta\mathbf{1}(Treated)_f \times \mathbf{1}(Post)_t + \mathbf{1}(Treated)_f + \kappa_g + \gamma_\delta$ using a matched sample. The dependent variable in column (1) (2) is the loan interest rate, the dependent variable in column (3) (4) is the total loan costs. The independent variable is an interaction term between the indicator for treated loans $\mathbf{1}(Treated)_f$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the loan amount of the refinance loans, the amount, interest rate, term and age of the previous loans, matched groups fixed effect, event year fixed effects, and the treatment status. Treated loans are refinance loans of households whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated loan is matched to control loans, which are comparable refinance loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a lender M&A shock. Standard errors clustered at the matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Interest Rate(%)		Total Loan Costs(k)	
Treated × Post	-0.0029	-0.0024	-0.0503	-0.1295
	(0.0150)	(0.0150)	(0.3029)	(0.2890)
Controls		YES		YES
Matched Group FE	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES
Treated	YES	YES	YES	YES
Observations	33109	33109	5847	5847
R^2	0.889	0.890	0.506	0.531

Table 5: Refinancing with New Lenders Not Reliant on Soft Information Sharing

This table reports the coefficients of $Refi\ w.\ New\ Lender \times Lender\ type_{i,t} = \alpha + \beta\mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable in column (1) (2) takes one if a household refinances with new lenders that are nonlocal depositories, the dependent variable in column (3) (4) takes one if a household refinances with new lenders that are fintech lenders. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi w. New Lender × Nonlocal Deps.		Refi w. New Lender × Fintechs	
Treated × Post	-0.0009***	-0.0011***	-0.0008***	-0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Controls		YES		YES
Household FE	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES
Observations	603098	603098	603098	603098
R^2	0.123	0.125	0.124	0.126

Table 6: Mortgage Refinancing Probability by Post-M&A Branch Changes

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using subsamples of a matched sample. The matched sample is splited based on the target lenders' post-M&A local branch changes. The target lenders refer to the treated households' relationship lenders, which, by construction, are the lenders being acquired. Column (1) reports results using the subsample in which over 50% of the target lender's branches in the county as of event year -1 are closed within four years post-M&A. Column (2) reports results using the subsample in which over 50% of the target lender's branches in the county as of event year -1 remain operational but are renamed within four years post-M&A. The dependent variable takes one if household i refinances in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

	$>$ 50% Branches Closed post M&A	$>$ 50% Branches Renamed post M&A
Treated × Post	-0.0294***	-0.0190***
	(0.0043)	(0.0027)
Controls	YES	YES
Household FE	YES	YES
Event Year FE	YES	YES
Observations	37161	75638
R^2	0.156	0.155
Differences	-0.0104**	
	(0.0051)	

Table 7: Cross-Sectional Heterogeneity: Interest Rate

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t=\delta)_t + \lambda \mathbf{1}(Treated)_i \times \mathbf{1}(t=\delta)_t \times Rate_t + Rate_t + \tau_i + \gamma_\delta$. The dependent variable takes one if household i refinances in year t. The independent variable in column (1) includes $Treat \times Post$, the market mortgage interest rate in year t, and its interaction with $Treat \times Post$. The independent variable in column (2) includes $Treat \times Post$, the one-year change in the market mortgage interest rate, defined as the difference between the rate in the current year t and the rate in the previous year $t-1$, and its interaction with $Treat \times Post$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi	
Treated × Post × Interest Rate(%)	0.0014***	
	(0.0005)	
Interest Rate(%)	-0.0035***	
	(0.0003)	
Treated × Post ×Δ Interest Rate(%)		0.0009
		(0.0006)
Δ Interest Rate(%)		-0.0030***
		(0.0004)
Treated × Post	-0.0299***	-0.0242***
	(0.0025)	(0.0010)
Controls	YES	YES
Household FE	YES	YES
Event Year FE	YES	YES
Observations	603098	603098
R^2	0.154	0.153

Table 8: Cross-Sectional Heterogeneity: Relationship Lender Characteristics

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta\mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \lambda\mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t \times RL_i + \tau_i + \gamma_\delta$. The dependent variable takes one if household i refinances in year t. The independent variable in column (1) includes $Treat \times Post$ and an interaction term between $Treat \times Post$ and the target lender's number of branches per 100,000 population in the county in event year -1. The target lenders refer to the treated households' relationship lenders, which, by construction, are the lenders being acquired. The independent variable in column (2) includes $Treat \times Post$ and an crossing term between $Treat \times Post$ and the target lender's share of total assets among all U.S. depository institutions, in units of percentages, in event year -1. The independent variable in column (3) includes crossing terms between $Treat \times Post$ and the target lender's type. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi		
Treated × Post × Branch	-0.0028***		
	(0.0009)		
Treated × Post × Size		0.0424**	
		(0.0201)	
Treated × Post × National Bank			-0.0165***
			(0.0034)
Treated × Post × Domestic Entity Other			-0.0252***
			(0.0013)
Treated × Post × State Chartered Bank			-0.0287***
			(0.0022)
Treated × Post × Other			-0.0224***
			(0.0026)
Treated × Post	-0.0194***	-0.0239***	
	(0.0018)	(0.0022)	
Controls	YES	YES	YES
Household FE	YES	YES	YES
Event Year FE	YES	YES	YES
Observations	231584	255323	496417
R^2	0.152	0.152	0.154

Table 9: Structural Estimation Results

This table reports the structural estimation results. Panel A reports the parameter estimates from the structural estimation. Column (1) reports the parameters in asleep probability χ, column (2) reports the parameters in loyalty advantage ϕ, column (3) reports the household's sensitivity to the mortgage payments μ, and column (4) reports the parameters governing the likelihood of entering alternative-motive-refinancing state ρ. Standard errors derived from the hessian matrix are reported in parentheses.* <0.1 ** <0.05 *** <0.01. Panel B reports the parameter-implied effects. Column (1) reports the parameter-implied awake probability $1 - w$ following equation 5, column (2) reports the parameter-implied loyalty advantage ϕ following equation 9, column (3) reports the household's sensitivity to the mortgage payments μ, and column (4) reports the parameter-implied likelihood of entering alternative-motive-refinancing state p_e following equation 6. For each row, Baseline refers to the implied effects when only the constant is considered. The Average Marginal Effect (AME) of a covariate refers to the average of the partial derivatives of the effect with respect to that covariate across all observations.

Panel A: Parameter Estimates				
	χ	ϕ	μ	ρ
w. Deps.				
Cons.	2.6821***	-0.1980		
	(0.0225)	(0.2082)		
Branch	-0.0660***	-0.0628		
	(0.0072)	(0.0640)		
Size	0.0262***	0.1990***		
	(0.0030)	(0.0259)		
w. NonDeps.				
Cons.	2.6837***	-1.3224***		
	(0.0118)	(0.0346)		
Cons.			0.1384***	3.4625***
			(0.0075)	(0.0105)

Panel B: Parameter-Implied Effects				
	Awake Probability $1 - w$	Loyalty Advantage κ	Sens. to Payments μ	Other-Motive-Refi. p_e
w. Deps.				
Baseline	0.0640	-0.1980		
AME of Branch	0.0039	-0.0628		
AME of Size	-0.0015	0.1990		
w. NonDeps.				
Baseline	0.0639	-1.3224		
Baseline			0.1384	0.0304

Appendix

A1 Data Matching Details

A1.1 HMDA & Verisk

I supplement the Verisk data with loan costs, borrower income and loan type from HMDA. **HMDA** is a loan-level dataset that covers nearly the entire universe of U.S. mortgage originations and applications. HMDA reports loan year, loan amount, property's census tract, lender throughout the sample period, and includes loan term starting in 2018.

I merge HMDA loan originations from 2003 to 2023 with Verisk loans using exact matching on loan year, loan amount, property's census tract, lender, and, when applicable, loan term. Following HMDA rounding policies, amount is rounded to the nearest $1,000 before 2017 and to $5,000 after 2018. HMDA uses different delineations of census tracts over time; I adjust for these changes accordingly: 2020 block to 2010 tract use the NHGIS crosswalks, 2020 block to 2000 tract use the Census Relationship Files. Verisk lender names with more than 100 mortgages in the full sample are retained, thereby removing non-institution lenders such as individuals. These Verisk lender names are then matched to HMDA lender names using fuzzy string matching.

To ensure accuracy, only one-to-one matches are kept.

A1.2 GSE & HMDA

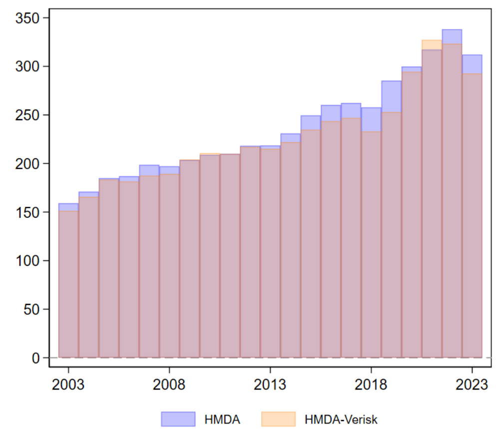
I supplement the Verisk data with loan performance information from the Freddie Mac and Fannie Mae Single Family Loan Performance Data (Government-Sponsored Enterprise, **GSE** data). The GSE data provides information on the GSEs' portfolios of fully amortizing, full documentation, single-family, fixed-rate mortgages.

The GSE data are matched with HMDA using a matching approach adapted from in Buchak and Jørring (2021) with modifications. Specifically, I merge GSE and HMDA loans through exact matching on loan year, zip code, loan amount, loan purpose, occupancy type, construction method, purchaser type, lender, and, when applicable, loan term, interest rate, total units, and prepayment penalty. HMDA census tracts are mapped to GSE zip codes using crosswalks. 2020 census-to-zip and 2010 census-to-zip crosswalks are obtained from the Census Relationship Files, and the 2000 census-to-zip crosswalks are from the HUD-USPS ZIP Code Crosswalk files. The GSEs report the seller as the entity that sold the mortgages to them. The seller name is disclosed only for sellers with a total original unpaid principal balance (UPB) representing 1% or more of the total original UPB of all loans in the dataset for a given quarter. Otherwise, the seller name is recorded as "Other Sellers"/"Other". GSE sellers are matched to HMDA originators under two cases. First, for disclosed sellers, I manually match GSE lenders to HMDA originators by names (include checking for any renamings) and closeness in market share ranks. I then carefully verify and exclude any candidate pairs involved in M&As. For example, GSE loans with the seller recorded as "truist bank formerly suntrust bank" are excluded from matching because the seller cannot be unambiguously attributed to a single pre-merger entity. For sellers reported as "Other", by construction, they cannot correspond to any disclosed seller in the same quarter. Accordingly, I delete any loan-level candidate matching pairs where the GSE seller is recorded as "Other" and its HMDA counterparts can also be matched to a disclosed GSE seller in the same quarter. HMDA reports loan term and interest rate starting in 2018.

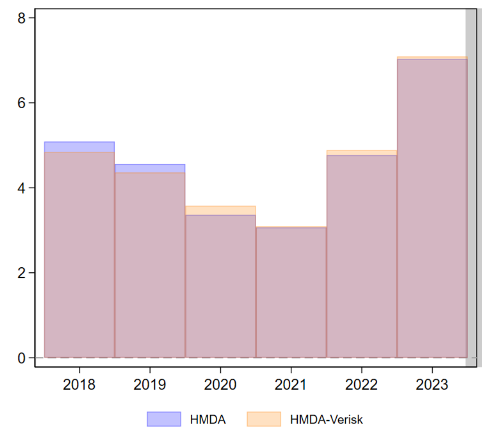
To ensure accuracy, only one-to-one matches are kept.

A2 Verisk-HMDA Data vs HMDA Data

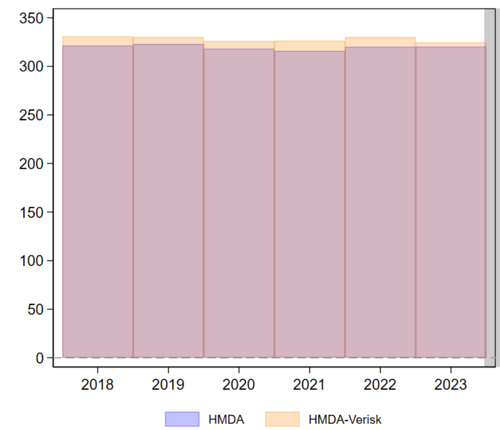
This section compares the yearly average loan amount, loan term, and loan interest rate between Verisk-HMDA Data and HMDA Data. HMDA reports loan amount throughout the sample period, and includes interest rate and loan term starting in 2018.



(a) Loan Amount (k)



(b) Loan Interest Rate (%)



(c) Loan Term (month)

A3 Definition of Relationship Lender

In the empirical tests, the relationship lender is defined as the originator of the existing mortgage.

Mortgage loans and mortgage servicing rights can be sold to other entities. Ex ante, it is unclear whether the lender-household relationship transfers when the loan ownership or servicing rights are transferred. I provide suggestive evidence using a subsample in which both loan originators and servicers can be observed but differ, with servicing lender data collected from the GSE data. Conditional on a new refinance loan, the probability of refinancing with the originators is 32%, while the probability of refinancing with the servicers is 11%. A t-test on the null hypothesis that these two probabilities have equal mean is rejected at p-value of 0.00. This pattern suggests that borrowers tend to maintain relationships with the originators, possibly because the loan application and origination process involve intensive interaction and communication between them.

Households switch lenders from time to time. Ex ante, it is unclear whether households tend to develop relationships primarily with their most recent lender, or maintain relationships with multiple lenders. I provide suggestive evidence using a subsample of borrowers who had originated mortgages with two different lenders in the past. Conditional on a new refinance loan, the probability of refinancing with the most recent lender is 25%, while the probability of refinancing with the second most recent lender is 19%. A t-test on the null hypothesis that these two probabilities have equal mean is rejected at p-value of 0.00. The results suggest households tend to develop relationships primarily with their most recent lender.

A4 Examples: Lender M&As Disrupt Relationships

M&A Lenders' Branch Changes

Among the M&As matched with loan-level data, I collect information on branch changes after the M&As for depository lenders covered by the SOD.

M&As may lead to branch shutdowns or renamings, both of which can disrupt lender-household relationships. Branch closures can weaken communication and trust, while branch renamings may also erode trust if borrowers are loyal to the original brand. Table A1 Panel A summarizes, across the acquired lenders, how their branches changed in the year following the M&As, among branches that existed one year prior to the M&As. On average, 43% of acquired lenders' branches were closed, and 54% of branches remained active but were renamed. Panel B summarizes, across the acquiring lenders, how their branches changed in the year following the M&As, among branches that existed one year prior to the M&As. By contrast, only 8% of acquiring lenders' branches were closed, and 19% of branches remained active but were renamed.

Overall, it suggest that after the M&As, acquired lenders experience substantial organizational changes that may disrupt relationships. This disruption tends to be more pronounced on the acquired lenders' side than on the acquiring lenders' side.

Table A1: M&A Lenders' Branch Changes

This table summarizes branch changes after the M&As for lenders that are covered by the SOD and involved in M&As that are matched with the loan-level data. Panel A summarizes, across the acquired lenders, how their branches changed in the year following the M&As, among branches that existed one year prior to the M&As. Panel B summarizes, across the acquiring lenders, how their branches changed in the year following the M&As, among branches that existed one year prior to the M&As.

Panel A: Acquired Lenders' Branches				
	Mean	Median	SD	N
N. branches pre M&A	46.1143	7.0000	227.9187	315
% Closed post M&A	43.1346	33.3333	38.9825	315
% Active & Renamed post M&A	54.4258	66.6667	39.4087	315
% Active & Same-Name post M&A	2.4396	0.0000	13.8413	315
Panel B: Acquiring Lenders' Branches				
	Mean	Median	SD	N
N. branches pre M&A	310.9595	48.5000	882.6190	296
% Closed post M&A	8.3962	5.1911	13.9536	296
% Active & Renamed post M&A	19.0861	0.0000	37.2939	296
% Active & Same-Name post M&A	72.5177	93.1426	39.2622	296

Examples from News Report

In 2022, Truist transitioned around seven million legacy SunTrust customers to a new digital system and rebranded 2,000 branches following the merger. The integration was criticized for poorly executed technological migration and inadequate customer communication, leading to widespread customer dissatisfaction. Kline (2022) report that customers reported difficulties using certain features of mobile and online banking, as well as frequent service disruptions. Customer support also deteriorated. Some customers reported waiting hours to speak with a representative, or never reaching one at all. Others reported that even branch managers could not offer a solution. In the month following the integration, the number of complaints filed against Truist with the Consumer Financial Protection Bureau (CFPB) increased by more than 81% relative to that in the month preceding the integration.

AMERICAN BANKER

Truist reckons with customer backlash after integration snags

May 11, 2022

"It's been extraordinarily frustrating and confusing," said Branden Lisi, a small-business owner who was on hold for hours trying to order a business credit card for one of his store managers.
Lisi, who opened a SunTrust business account in 2007 when his company expanded to Atlanta, did not wind up filing any complaints against Truist. But **he's now looking for a new bank,** he said.
…
Last month, John Runyan, who became a SunTrust customer in 1984, tweeted Truist directly after a business check that he deposited into his Truist account was put on a 10-day hold. His message: "**It took Truist just two [months] after taking over Suntrust to end our 38-year banking relationship.** You cashed my deposit, you were paid, but your branch manager can't free the funds for 10 days and I can't phone staff. See you later…"
…
"So she goes into a branch in Alexandria [Virginia] and I go into a branch on Capitol Hill and **neither branch manager could offer a solution**," said Runyan, who runs a public affairs consulting firm.
"**There was nothing they could do**. Every ounce of authority had been taken away."

Figure A1: Example of a Lender M&A: Truist & SunTrust

Another example is the 2024 transfer of First Republic customers to JPMorgan Chase following the M&A, in which customers complained about the service disruptions and terrible communication (Saeedy, 2024).

THE WALL STREET JOURNAL.

They Were Used to Five-Star Service at First Republic. Now They're Just Regular Customers.

Account holders gripe after bumpy early experiences with the bank's new owner, JPMorgan Chase

May 30, 2024

Across Silicon Valley, where **First Republic was legendary** for its concierge services, personal bankers, cheap mortgages and umbrellas, people such as tech executive Pieter Nel were shocked to realize that **they are now run-of-the-mill Chase customers.**

…

"Despite months of planning, **JPMorgan is failing miserably at the simple task of transferring former First Republic Bank accounts**," he wrote in a post on X. "That includes the embarrassment of having your card declined for transactions, despite assurances that everything would work smoothly."

Figure A2: Example of a Lender M&A: JPMorgan Chase & First Republic

A5 Examples: Relationship-Lender-Informing

The figure A3 reproduces a real email sent by a loan officer to his relationship customers, with personal information redacted.

Subject: [Customer], **I Just Ran the Numbers. You Could Be Paying Too Much.**
Sent: [date], 2025

Hi [Customer],

I wanted to personally reach out because I reviewed your loan, and **there's a real chance I can help you save money on your mortgage,** but I need your permission to take the next step. Sometimes, even small changes can make a big difference in your monthly budget.

Let's take a look together. Call or text me at [Phone Number].

Looking forward to helping you take the next step,
[Mortgage Company]
[Loan officer]

Figure A3: A Real Email from the Relationship Lender

The figure A4 provides news examples in which relationship lenders inform borrowers about potential refinancing opportunities.

Source: *The Washington Post, October 17, 2014*

As soon as lenders saw signs of rates plummeting Wednesday, **they began reaching out to homeowners in a furious burst of phone calls and e-mails**.

…

This week, they locked in a 3.5 percent rate, half a percentage point lower than the rate on their current loan. "We have a little more value. We've paid down a little more principal, and we're able to take advantage of the low rates," Calderwood said. "**My lender reached out to me to tell me what's going on**, and I just passed the news along to everyone I knew."

Source: *wxyz.com, August 20, 2020*

In the last few days, several benchmark mortgage refinance rates trended upwards, but they remain low by historical standards, which is why loan experts say you should at least consider locking in a new rate and locking down huge savings.
"**My lender called me and said you're gonna want to take advantage of this**," said Jennifer Amolsch.

Figure A4: News Examples of Relationship-Lender-Informing

Sources: https://www.washingtonpost.com/news/get-there/wp/2014/10/17/the-drop-in-mortgage-rates-created-a-frenzy-of-refinancing-should-you-jump-in/ (First article);
https://www.wxyz.com/rebound/coronavirus-money-help/rebound-detroit-is-it-a-good-time-to-refinance-during-the-pandemic-experts-weigh-in (Second article).

A6 The National Survey of Mortgage Originations

The National Survey of Mortgage Originations (NSMO) is a mail survey managed by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB). It surveys a nationally representative sample of newly originated closed-end first-lien residential mortgages in the United States.

From the first quarter of 2014 to the second quarter of 2022, the NSMO surveyed 25,214 borrowers whose mortgages were to refinance or modify an earlier mortgage. The survey includes a question asking, "How much did you use each of the following sources to get information about mortgages or mortgage lenders?". For each source, respondents could choose from three options "A lot", "A little", or "Not at all". Figure A5 plots those refinancing borrowers' main information sources. A source is classified as a main information source if the respondent selected "A lot". The respondents' mortgage lenders or brokers overwhelmingly stand out. 69% of respondents selected "Your mortgage lender/broker" as a main information source, over three times the frequency of the second most common source, "Websites on getting a mortgage" (20%), and nearly five times that of the third, "Bankers, credit unions or financial planners" (14%). These responses highlight that relationship lenders serve as a primary and dominant information source for refinancing borrowers.

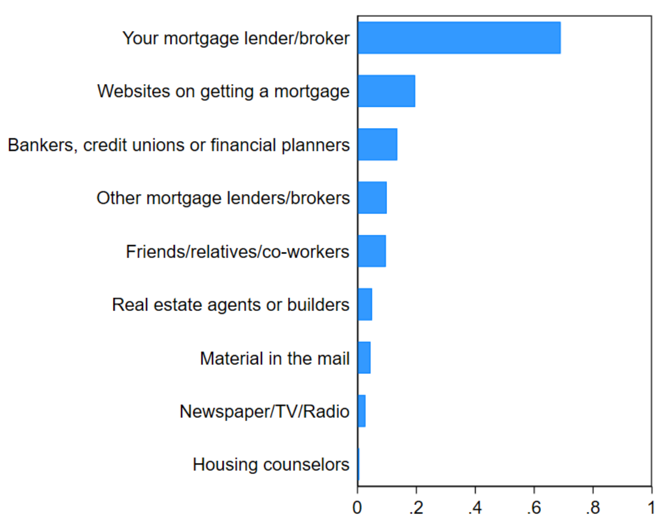


Figure A5: Refinancing: Main Information Sources about Mortgages or Mortgage Lenders

The survey also asked,“How many different mortgage lenders/brokers did you seriously consider before choosing where to apply for this mortgage?”. Conditioning on borrowers whose mortgages were to refinance or modify an earlier mortgage and whose main information source was “Your mortgage lender/broker” (17,395 respondents), Figure A6 presents the responses. 46% of respondents considered more than one lender for refinancing. This suggests that, after receiving refinancing information, borrowers will consider refinancing opportunities broadly, including those with their relationship lenders or with new lenders.

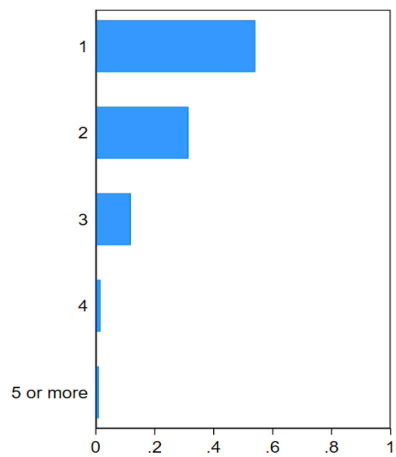


Figure A6: Refinancing Borrowers Who Rely on Their Lender/Broker for Information: Number of Lenders/Brokers Considered for Refinancing

A7 Mortgage Refinancing Probability: Robustness

A7.1 Acquirer-Matched Sample

I re-estimate specifications 1 and 2 using the Acquirer-Matched Sample, in which the control group not only satisfies the matching criteria in main sample, but also consists only of households whose relationship lender is the corresponding acquiring lender.

Table A2: Mortgage Refinancing Probability: Acquiror-Matched Sample

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using an Acquiror-Matched sample. The dependent variable in column (1) (2) takes one if household i refinances in year t, the dependent variable in column (3) (4) takes one if household i refinances with the relationship lender in year t, the dependent variable in column (5) (6) takes one if household i refinances with a new lender in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households whose relationship lender is the corresponding acquiring lender, located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi		Refi w. Rel. Lender		Refi w. New Lender	
Treated × Post	-0.0153***	-0.0181***	-0.0093***	-0.0110***	-0.0060***	-0.0072***
	(0.0018)	(0.0019)	(0.0012)	(0.0012)	(0.0014)	(0.0014)
Controls		YES		YES		YES
Household FE	YES	YES	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES	YES	YES
Observations	173038	173038	173038	173038	173038	173038
R^2	0.124	0.150	0.134	0.146	0.122	0.141

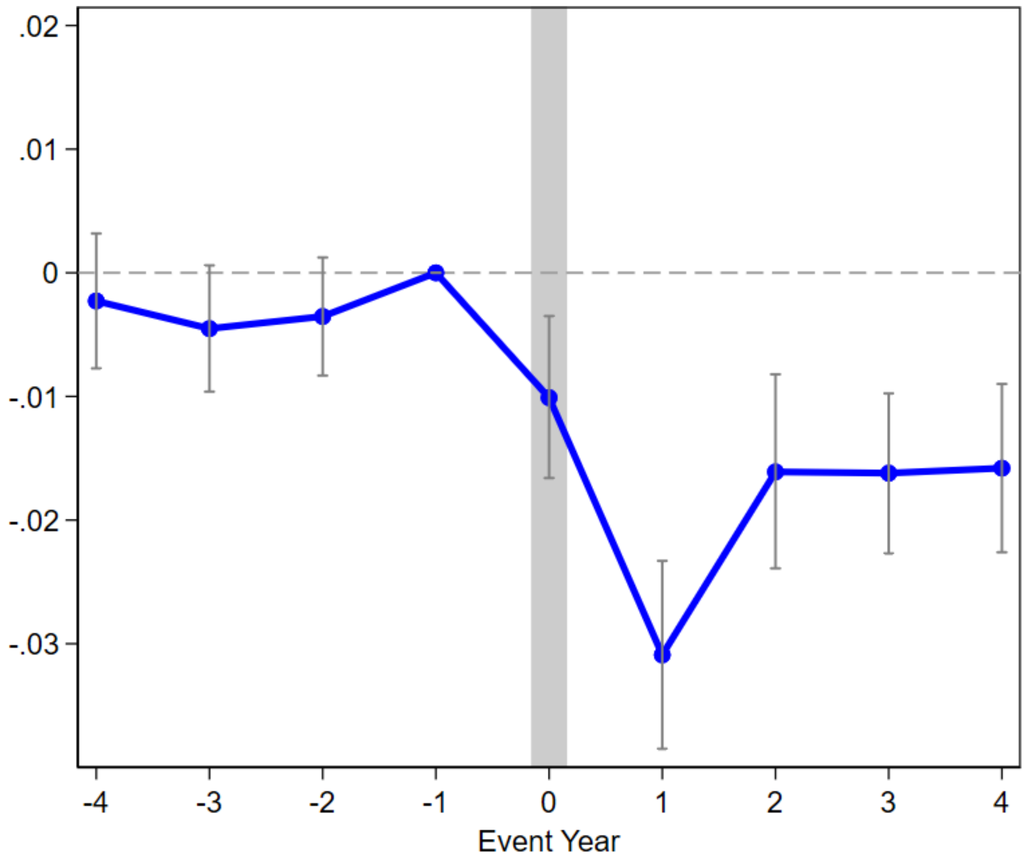


Figure A7: Mortgage Refinancing Probability: Acquiror-Match Sample

Note: This Figure plots the coefficients of $Refi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using an Acquiror-Matched sample. The dependent variable $Refi_{i,t}$ takes one if household i refinances in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t = \delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households whose relationship lender is the corresponding acquiring lender, located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.

A7.2 Verisk-HMDA Sample

I re-estimate the specifications using only the Verisk-HMDA matched loans, which allows me to replace my classification with HMDA's refinance flag. This sample also enables additional controls for loan type and borrower income. I further restrict the sample to households holding conventional loans prior to the shock and include borrower income in the propensity score matching. I also include loan type and borrower income of the existing loan in the regression controls.

Results show that the overall refinancing probability decreases by 42% relative to the Verisk–HMDA sample mean of 0.0144. The probability of refinancing with new lenders decreases by 48% relative to the Verisk–HMDA sample mean of 0.0073, confirming the robustness of the main findings.

Table A3: Mortgage Refinancing Probability: Verisk-HMDA Sample

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample consisting of Verisk-HMDA matched loans. The dependent variable in column (1) (2) takes one if household i refinances in year t, the dependent variable in column (3) (4) takes one if household i refinances with the relationship lender in year t, the dependent variable in column (5) (6) takes one if household i refinances with a new lender in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, loan type, borrower income, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi		Refi w. Rel. Lender		Refi w. New Lender	
Treated × Post	-0.0046***	-0.0060***	-0.0019***	-0.0026***	-0.0027***	-0.0035***
	(0.0007)	(0.0007)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Controls		YES		YES		YES
Household FE	YES	YES	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES	YES	YES
Observations	288574	288574	288574	288574	288574	288574
R^2	0.128	0.158	0.131	0.143	0.127	0.147

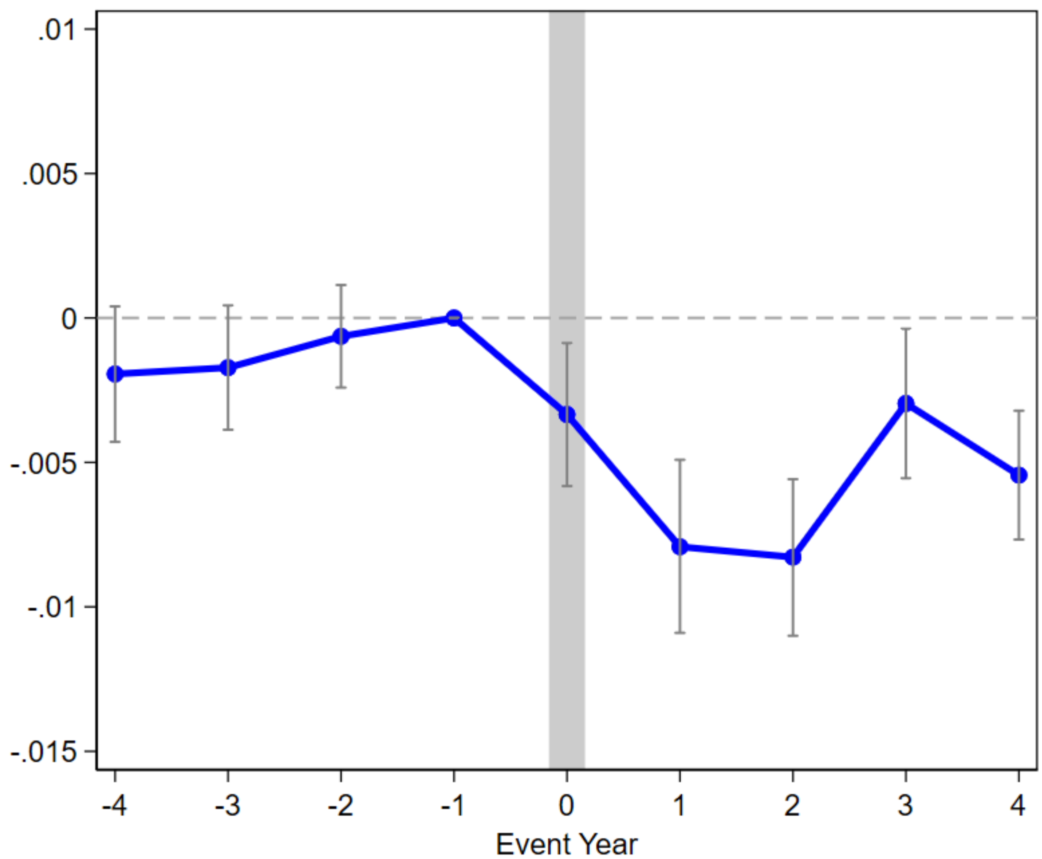


Figure A8: Mortgage Refinancing Probability: Verisk-HMDA Sample

Note: This Figure plots the coefficients of $Refi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t=\delta)_t + \tau_i + \gamma_\delta$ using a matched sample consisting of Verisk-HMDA matched loans. The dependent variable $Refi_{i,t}$ takes one if household i refinances in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t=\delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.

A7.3 Controlling Lender Characteristics

I control for lender characteristics in both the propensity score matching and the regression specifications. The lender characteristics include the relationship lender's market share, the share of refinance loans among its mortgage originations, and the share of mortgages that remained unsold at the time of reporting.

Table A4: Mortgage Refinancing Probability: Controlling Lender Characteristics

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable in column (1) (2) takes one if household i refinances in year t, the dependent variable in column (3) (4) takes one if household i refinances with the relationship lender in year t, the dependent variable in column (5) (6) takes one if household i refinances with a new lender in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term; the relationship lender's market share, the share of refinance loans among its mortgage originations, and the share of mortgages that remained unsold at the time of reporting; household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Refi		Refi w. Rel. Lender		Refi w. New Lender	
Treated × Post	-0.0201***	-0.0244***	-0.0128***	-0.0155***	-0.0073***	-0.0089***
	(0.0012)	(0.0013)	(0.0008)	(0.0008)	(0.0009)	(0.0010)
Controls		YES		YES		YES
Household FE	YES	YES	YES	YES	YES	YES
Event Year FE	YES	YES	YES	YES	YES	YES
Observations	374304	374304	374304	374304	374304	374304
R^2	0.128	0.161	0.127	0.145	0.132	0.148

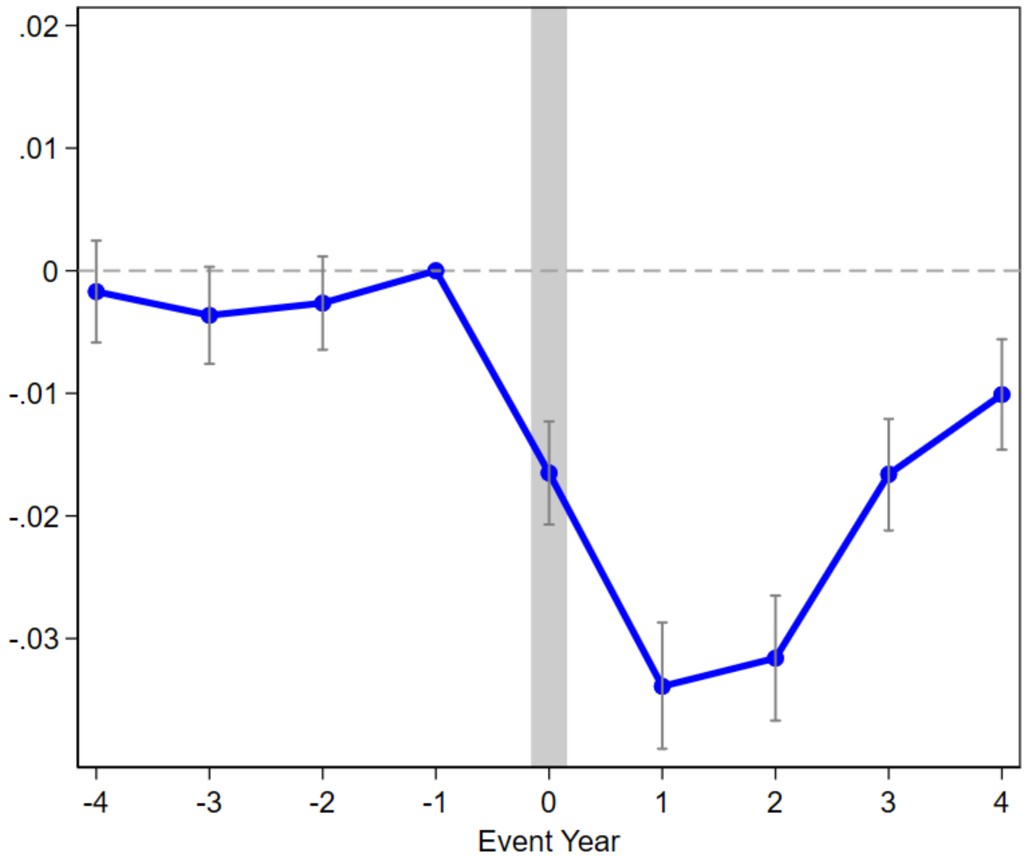


Figure A9: Mortgage Refinancing Probability: Controlling Lender Characteristics

Note: This Figure plots the coefficients of $Refi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable $Refi_{i,t}$ takes one if household i refinances in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t = \delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.

A8 Loan Performance: Robustness

I examine the performance of all loans, including both refinance and non-refinance loans. This allows me to assess borrower quality without conditioning on the decision to refinance. The results confirm no significant differences in borrower quality.

Table A5: Loan Performance

This table reports the coefficients of $Loan\ Delinquent_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable takes one if the household i's loan was ever 90 or more days delinquent on monthly payments in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

Y =	Loan Delinquent	
Treated × Post	-0.0068	-0.0052
	(0.0069)	(0.0070)
Controls		YES
Household FE	YES	YES
Event Year FE	YES	YES
Observations	15534	15534
R^2	0.443	0.445

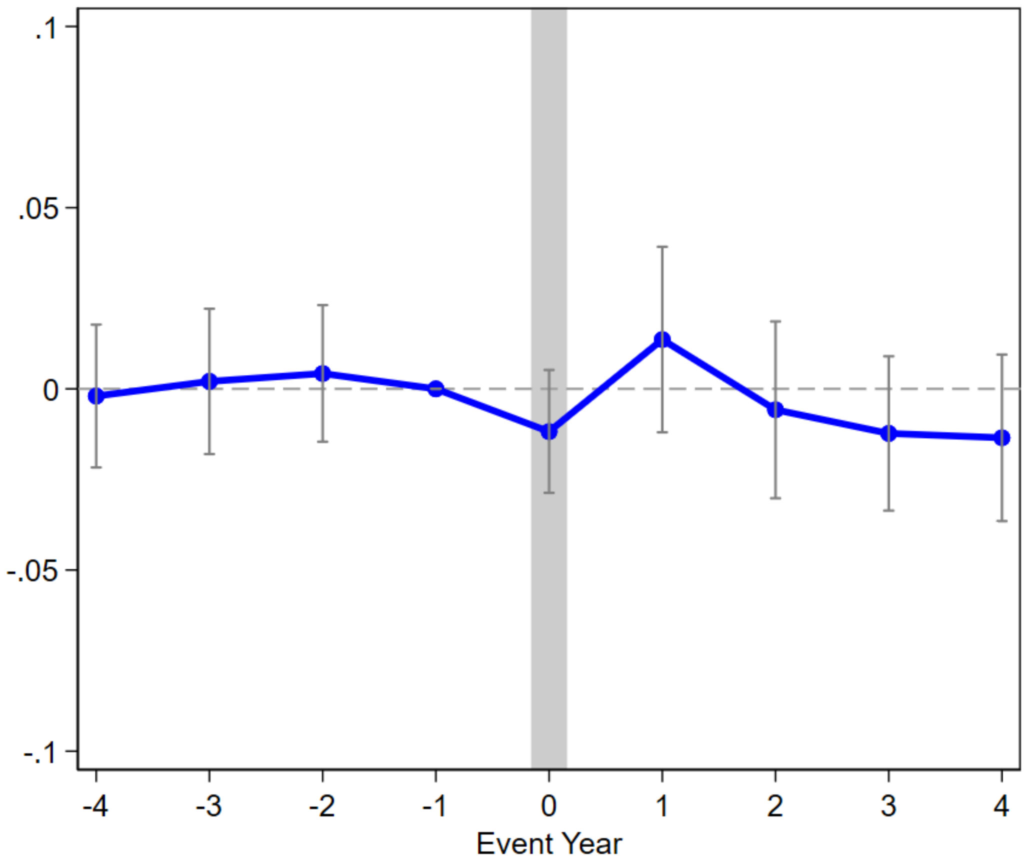


Figure A10: Loan Performance

Note: This Figure plots the coefficients of $Loan\ Delinquent_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable takes one if the household i's loan was ever 90 or more days delinquent on monthly payments in year t, the independent variables are interaction terms between an indicator for treated households $\mathbf{1}(Treated)_i$ and indicators for event years $\mathbf{1}(t = \delta)_t$. The regression includes household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock.

A9 Subsample by Borrower Income

This test splits the main sample into high- and low-income groups based on the treated households' most recent reported income prior to the shock, within the same state and income-reporting year.

Table A6: Mortgage Refinancing Probability by Borrower Income

This table reports the coefficients of $Refi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using subsamples of a matched sample. The matched sample is splited into high- and low-income groups based on the treated households' most recent reported income prior to the shock, within the same state and income-reporting year. The dependent variable takes one if household i refinances in year t. The independent variable is an interaction term between the indicator for treated households $\mathbf{1}(Treated)_i$ and an indicator for the post-event period $\mathbf{1}(Post)_t$. Controls include the existing mortgage's amount, interest rate, age, term, household by matched group fixed effects and event year fixed effects. Treated households are those whose relationship lender was acquired, with the M&A year designated as event year zero. The relationship lender is defined as the originator of the existing mortgage. Each treated household is matched with control households located in the same county, holding comparable existing loans prior to the lender M&A shock, but never experienced a lender M&A shock. Standard errors clustered at the household by matched group level are reported in parentheses.* <0.1 ** <0.05 *** <0.01.

	Low Income Household	High Income Household
Treated × Post	-0.0279***	-0.0275***
	(0.0015)	(0.0018)
Controls	YES	YES
Household FE	YES	YES
Event Year FE	YES	YES
Observations	208552	194323
R^2	0.154	0.156
Differences	0.0004	
	(0.0023)	