How Do Lender-Household Relationships Affect Mortgage Refinancing?*

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Abstract

What role do lenders play in household refinancing? This paper provides insights into this question using a unique dataset that tracks lender-household relationships for about 25 million mortgage loans. The empirical results show that an exogenous disruption to lender-household relationships substantially reduces a household's refinancing probability by 69.45%. In particular, rather than switching to new lenders, the probability that a household refinances with new lenders also declines by 51.91%. The disruption of relationships does not affect refinance loans' interest rates, fees, or performance. The evidence is consistent with the channel that relationship lenders help households refinance by providing information about potential refinancing opportunities. The paper further develops a structural model in which relationships affect households' awareness of refinancing opportunities and refinancing costs simultaneously.

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1 Introduction

Mortgage refinancing is an important tool for households to manage debts, and also serves as a key transmission channel for monetary policy. However, households often refinance suboptimally. A large literature has explored the reasons from the borrower side, including factors such as inattention, suspicion of lender motives, and search costs (Andersen et al., 2020, Byrne et al., 2023, Johnson et al., 2019, Keys et al., 2016, Ambokar and Samaee, 2019). Yet few studies examine the role lenders play in household refinancing behavior. This paper provides new evidence on this question.

This paper asks how lender-household relationships affect mortgage refinancing. The lender-household relationships refer to relationships established through interactions between lenders and households, which may involve building trust and sharing information. This paper aims to investigate the causal effect of lender-household relationships on household refinancing, including refinancing probability and the characteristics of refinance loans.

To study this question, data containing both household refinancing behavior and lender-household relationship is required. This paper constructs a unique loan-level dataset with household identifiers by merging data from the Home Mortgage Disclosure Act (HMDA) and Verisk. HMDA provides loan-level data that covers nearly the entire universe of U.S. mortgage originations. However, HMDA does not contain household identifiers and therefore cannot be used to track a household's relationships with lenders over time. To overcome this limitation, I supplement HMDA with property-level mortgage history data from Verisk. The merged dataset enables me to track lender-household relationships over time for approximately 25 million mortgages.

To identify 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 to control households located in the same county, holding comparable existing mortgages prior to the lender M&A shock, and have never experienced a lender M&A shock.

Lender M&As plausibly disrupt lender-household relationships across at least three dimensions: disrupting communication, eroding customer trust, and losing soft information. Firstly, M&As disrupt communication between lenders and their customers. M&As usually involve the integration of online platforms and IT systems. Adjusting to a new digital platform can be time-consuming and confusing for customers, making it difficult for them to stay updated on information from their lenders. Besides technological disruptions, M&As often lead to the replacement of the acquired lender's management and loan officers, and may also involve branch restructuring or closures. Surveys find that mortgage borrowers particularly value advice from lenders and interpersonal interactions with local officers (Valenti and Alderman, 2021). M&As could disrupt these communication channels that customers rely on. Secondly, M&As may erode customer trust. Customers face uncertainty about account changes, new digital tools, and potential service interruptions during integrations. Poor customer assistance can leave customers feeling skeptical about the security and stability of their lenders. Lastly, M&As can result in the loss of soft information. The relationship facilitates the accumulation of soft information, which is valuable for customers who lack sufficient hard information to signal their quality. M&As-induced loan officer replacement or branch shutdown will lead to the loss of officers who possess such soft information. Allen et al. (2016) use bank M&As as an exogenous shock to bank-customer relationships, focusing on loss of soft information.

Overall, lender M&As may disrupt lender-household relationships. Several recent cases provide supporting evidence. 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 poor technological migration and inadequate customer support. Two months after the integration, the number of complaints filed against Truist with the Consumer Financial Protection Bureau (CFPB) increased by more than 81%, and there were reports of customers ending decade-long banking relationships due to the frustrating experience. In 2024, the transfer of First Republic customers to JPMorgan Chase following a M&A was also criticized for service disruptions and insufficient communication.

To qualify as an exogenous shock to lender-household relationships, lender M&As must be independent of other factors that might influence household refinancing, including local economic conditions and refinance contracts offered to households, conditional on the matched sample. While lender M&As and local economic conditions might be correlated, for example if the local area is a major market for the lender, conditional on a sample matched on county, the M&As are plausibly exogenous. The second concern is whether lender M&As would impact the refinance contracts offered to households. For example, 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 ensures that treated and control households are exposed to the same competitive environment. Another possibility is that M&As may affect the acquiring lenders' loan offerings to customers. For example, the acquiring lenders may change their loan approval criteria or contract terms after the M&As. 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 loan offers after the M&As.

The results show that the exogenous disruption to lender-household relationships substantially reduces household refinancing probability. Treated households are 69.45% less likely to refinance compared to control households in the post-event period. Importantly, rather than switching to new lenders, the probability that a treated household refinances with new lenders also declines by 51.91% compared to control households. 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.

Overall, maintaining lender-household relationships helps households refinance in improving refinancing probability, without impacting refinancing costs or screening standards.

Several potential channels might explain how lender-household relationships help households refinance. First, relationship lenders can inform borrowers of potential refinancing opportunities. Lenders actively reach out to their relationship customers regarding potential refinancing opportunities in order to earn loan origination fees and maintain customer relationships. This connection has two important features: it is frequent, and it is trusted by borrowers, both of which are crucial for household refinancing decisions. Inattention is one of the reasons why households fail to react to low interest rates (Andersen et al., 2020). Byrne et al. (2023) show that simply sending a reminder letter to customers increases refinancing probability by 76% in a field experiment setting, consistent with the idea that customers are inattentive and a reminder can effectively reduce these frictions. Johnson et al. (2019) study why people did not take up favorable refinancing opportunities offered in a policy program, and they find that customer suspicion is the main obstacle, in which people receiving the offer doubted that the deals were "too good to be true". The communication from relationship lenders helps address both problems: it is frequent and serves as a reminder, and it is trusted by borrowers, making it particularly effective in informing households about refinancing opportunities. Alternative channels through which relationship lenders may help borrowers include cost advantages and soft information. Buchak et al. (2023) argue that certain lenders have a cost advantage in refinancing their servicing customers, which can lower customers' refinancing fees and enhance refinancing probability. In addition, relationship lenders may possess soft information about borrower quality, which has been shown to be important for both household and corporate financing in the literature (Allen et al., 2016 and A. N. Berger et al., 2024).

The evidence that disruptions in lender-household relationships generate a large negative spillover effect on household refinancing probability with new lenders is consistent with the informing channel: after the relationship breaks, households are less likely to be aware of potential refinancing opportunities and therefore less likely to refinance, regardless of with relationship lenders or new lenders. In contrast, the cost advantage channel predicts that if households lose access to a low-cost refinancing opportunity, they should switch to the next best refinancing opportunity, meaning they would be more likely to refinance with new lenders, or at least the likelihood would remain unchanged. This prediction is inconsistent with the empirical evidence. Similarly, the soft information channel predicts that if the loss of soft information makes them can no longer secure refinancing with the original lender, they would switch to other lenders. However, the empirical evidence strongly rejects this prediction as well. Additional evidence also fails to support the cost advantage or soft information channels. There are no changes in refinancing costs or loan performance following relationship disruptions, and subsample analysis shows no stronger effects among low-income households, who are more sensitive to costs and reliant on soft information. Overall, the findings are most consistent with the informing channel. Cross-sectional analysis further explores heterogeneity in the informing channel. Households with stronger incentives to monitor refinancing opportunities on their own, of younger age, with college education, and working in the financial industry tend to depend less on lenders' information.

While the reduced-form results are well identified, several important questions remain. First, this paper highlights a novel informing channel through which relationship lenders influence household refinancing. Prior literature has mainly focused on soft information or cost channels. A structural model that jointly considers these channels can clarify their relative importance and provide a more complete picture of how lender relationships shape refinancing behaviors. Second, refinancing is inherently a dynamic process. While the reduced-form evidence identifies effects from cross-sectional shocks, a structural model that incorporates this dynamic feature is necessary to understand how these effects unfold in an intertemporal context. Lastly, given the importance of refinancing, policies such as the Home Affordable Refinance Program were implemented to influence refinancing activity. The critical role of lenders in facilitating refinancing raises the question of whether lender-targeted policies could encourage households to refinance. Meanwhile, 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 ability of relationship lenders to inform borrowers about refinancing opportunities, thereby generating unintended adverse effects. Structural counterfactual analysis is essential to assess the potential impact of these policies on household refinancing. Accordingly, this paper further develops a structural model of lender-household relationships and household refinancing.

I use a mixture model adapted from Andersen et al. (2020). In each period, households go through two stages. In the first stage, each household enters one of two states: "awake" or "asleep". In the second stage, awake households choose which lender to refinance with, or choose not to refinance. Asleep households do not refinance. Central to the model is that lender-household relationships enter both stages: The relationships enter the first stage, impacting household awake probability. This captures the idea that relationship lenders provide information to the household, and thereby influence the household's probability of being attentive to potential refinancing opportunities. The relationships enter the second stage, impacting the utility that the household gets when refinancing with a particular lender. This reflects the idea that relationship lenders provide "value" (e.g., cost and soft information advantages/disadvantages) to the household and thus influence the household's choice of lender.

The estimation results demonstrate that lender-household relationships play a critical role in shaping the probability of households becoming attentive to refinancing opportunities, as well as the refinancing costs they face. Longer relationship durations substantially increase the household's awake probability. A household with a one-year relationship has an awake probability of 8.98%. As the relationship extends to 2–5 years, this probability more than doubles to 19.88%, and remains above 20% over longer durations. In contrast, the refinancing costs follow a U-shaped pattern over relationship duration. Compared with refinancing with a non-relationship lender at a cost of $3,957, households benefit from refinancing with a relationship lender during the early and middle stages, with costs as low as $898, but face higher costs as the relationship lengthens, reaching up to $5,941. Mortgage companies and credit unions perform markedly better than national banks and state-chartered banks in informing their relationship borrowers. The awake probabilities for households in relationships with these lender types are 16.33%, 14.29%, 8.98% and 10.35%, respectively. Meanwhile, mortgage companies impose very high additional refinancing costs of $27,230 on their relationship borrowers, compared with a more moderate cost of $2,252 for households in relationships with national banks. Credit unions charge the lowest additional refinancing costs, nearly zero.

In the counterfactual analysis of lender-targeted policies, a policy that improves lenders' ability to awaken borrowers to the level observed for mortgage companies increases the aggregate refinancing rate by 24%. Its effect is even more powerful than that of a policy directly reducing refinancing costs. In contrast, a policy that restricts lenders' outreach and lowers their ability to awaken borrowers to the level observed for national banks results in a 26% decline in the aggregate refinancing rate. This reduction raises 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 structural model of lender relationships and household refinancing. Section 5 concludes.

Related Literature

This paper aligns with the literature showing that frequent and trustworthy communication can help households refinance. Byrne et al. (2023) conduct a field experiment and find that simply sending a reminder letter can largely improve household refinancing probability. Johnson et al. (2019) find that suspicion is the main obstacle to households taking up favorable refinancing opportunities. In this context, relationship lenders have an advantage in informing borrowers about potential refinancing opportunities: their communication is frequent and serves as a reminder, and it is trusted by borrowers. A related finding in Buchak et al. (2023) is that fintech lenders can use technology to encourage customers to refinance, and fintech lenders utilize this customer acquisition ability to exploit market power, charging higher markups to loyal customers. While both papers find that lenders can prompt borrowers to refinance, the mechanisms and implications differ. Buchak et al. (2023) emphasize fintech lenders' technology as the key for facilitating borrower refinancing. By contrast, this paper identifies a more general mechanism present across all types of lenders: the provision of information, the effectiveness of which hinges on the relationships. More importantly, the implications differ. Buchak et al. (2023) find that fintech lenders particularly attract borrowers who are not considering other offers, thus generating market power and charging high markups. In contrast, this paper shows that information provision substantially increases borrowers' refinancing with other lenders, and the providers themselves do not gain market power. This indicates that borrowers affected by this channel, who comprise a broad group as long as they maintain relationships with lenders, do consider other lenders after receiving the information. Therefore, information provision improves 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 information provision.

This paper also relates to the literature examining how borrowers' loyalty to relationship lenders affects their mortgage or refinancing prices. Basten and Juelsrud (2023) and Allen et al. (2019) find that when customers stay loyal and originate mortgages with their relationship lenders, they are often charged higher prices. Buchak et al. (2023) find integrated lenders, defined as those acting as both originator and servicers, have a cost advantage when refinancing their existing customers. It allows their loyal customers to pay lower fees and become more likely to refinance. This paper is distinct from that strand of the literature in several important ways. The literature focuses on the consequences of borrower loyalty. In contrast, this paper examines the consequences of the presence of a lender-household relationship itself, rather than its persistence. To the best of my knowledge, this is the first paper to directly study how lender relationships impact household refinancing. This approach offers a more comprehensive understanding of the role lenders play in household refinancing. Beyond affecting pricing through market power or competition, relationship lenders may also create value through other mechanisms. In particular, this paper finds that relationship lenders are critical in providing information, a novel channel that is distinct from the literature focusing on pricing.

In addition, this paper contributes to the modeling of household refinancing. Some studies focus on households' refinancing decisions. For example, Agarwal et al. (2013) derive a closed-form optimal refinancing rule, and Andersen et al. (2020) develop a two-stage mixture model that incorporates both 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 adapts the inattention framework and highlights the importance of heterogeneous lender characteristics in shaping household refinancing.

More broadly, this paper connects to other studies examining lenders' impacts on refinancing. 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). This paper also broadly connects to lender-household relationships and household finance (Allen et al., 2016, Basten and Juelsrud, 2023,A. N. Berger et al., 2024).

2 Data

This paper constructs a unique loan-level dataset with household identifiers by merging data from the Home Mortgage Disclosure Act (HMDA) and Verisk, enabling the tracking of households' relationships with lenders over time.

HMDA is a loan-level dataset that covers nearly the entire universe of U.S. mortgage originations and applications. It is widely used in the literature. HMDA flags whether a loan is for refinancing, which is a key variable in the analysis and is 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". [1] Other variables collected from HMDA include loan origination year, loan amount, loan type (Conventional/FHA/VA/RHS or FSA); borrower income and location at the census tract level. Since 2018, HMDA also provides additional details including non-interest-rate charges (e.g., origination charges, discount points, and lender credits) and loan term. However, HMDA does not contain household identifiers and therefore cannot be used to track households' relationships with lenders over time. Moreover, several key outcome variables in this analysis, such as interest rate, are only provided in HMDA starting in 2018. To overcome these limitations, I supplement the analysis with data from Verisk.

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 characteristics and household demographic 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. It tracks an average of 25 years of historical data and ends in the latest year for which property taxes were billed (mostly 2023 in this data version). For each property, it provides details of the most recent three mortgages. I collect three types of information from Verisk: Property information, including a unique property ID, census block–level location, and the latest deed transaction date; Mortgage details of the most recent three mortgages, including mortgage date, loan amount, loan type (fixed or adjustable rate), loan term, and interest rate; Household demographics.

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

To ensure that each property corresponds to only one particular household, I retain only mortgage records dated no earlier than the most recent deed transaction date.

I merge loans in HMDA and loans in Verisk from 2003 to 2023, via exact matching on loan year, loan amount[2], property's census tract[3], and, when applicable, loan term. To ensure accuracy, only one-to-one matches are kept. The result is a loan-level dataset with household identifiers ("HMDA-Verisk Data"), covering approximately 25 million loans. To assess whether the merged sample is representative of the full mortgage sample, I compared the loans in the HMDA-Verisk data with those in the HMDA data in Appendix A1. The patterns in the merged sample are consistent with those in the full sample. 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%. Lastly, GSE single-family loan performance data are matched to the HMDA–Verisk data following the matching procedures in Buchak and Jørring (2021) to supplement loan performance information. Summary statistics of the HMDA–Verisk data are reported in Table 1.

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. 92% loans in the HMDA-Verisk Data were matched to NIC data via lender identifier crosswalk provided by the HMDA Panel. The M&A data includes the acquisition dates and the identities of the acquiring and acquired lenders. I restrict the sample to events where the acquired lenders ceased operating as independent entities.

[2]Rounded to the nearest $1,000 before 2017 and to $5,000 after 2018, following HMDA rounding policies

[3]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

3 Empirical Evidence

This section provides causal evidence on how lender-household relationships influence household mortgage refinancing. The first part discusses the effects on refinancing probability. The second part examines, conditional on refinancing, the effects on the refinance loans' costs and performance. Lastly, I discuss the underlying channels.

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. Specifically, the relationship lender is defined as the originator of the existing mortgage. [4] The treated households are those whose relationship lender was acquired, with the M&A 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 to 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 to treated households based on the year, property county, and the term and type 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, and borrower income of the existing mortgage in event year –1, as well as refinance

[4] Literature also uses the primary bank as a proxy for the relationship lender. I am not able to check this definition due to data constraints. Another proxy for relationship lenders could be the mortgage servicers. I test it in a subsample where both originators and servicers can be observed but differ, and find that households are three times more likely to refinance with the originators rather than with the servicers.

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

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, for the matched households, I examine their refinancing probability over a four-year window centered on the event year. The four-year window is chosen because the 20th percentile of the data length for the treated households is nine years.

Lender M&As may disrupt lender-household relationships by disrupting communication, eroding customer trust, and losing soft information. Firstly, lender M&As disrupt communication between lenders and their customers. M&As usually involve the integration of online platforms and IT systems. Adjusting to a new digital platform can be time-consuming and confusing for customers, making it difficult for them to stay updated on information from their lenders. The resulting confusion may also trigger a surge in customer inquiries, and if customer services fail to address these inquiries in a timely manner, communication difficulties can be further exacerbated. Besides technological disruptions, M&As often lead to the replacement of the acquired lender's management and loan officers, and may also involve branch restructuring or closures. Surveys find that mortgage borrowers particularly value advice from lenders and interpersonal interactions with local officers. [6] M&As can disrupt these communication channels that customers rely on. Secondly, lender M&As may erode customer trust. Reports show that customers often face uncertainty about account changes, new digital tools, and potential service interruptions during integration. Poor customer assistance can leave customers feeling "lost or skeptical" about the security and stability of their lenders. [7] Lastly, M&As can result in the loss of soft information. The relationship facilitates the accumulation of soft information, which is valuable for customers who lack

[6]For example, survey by Valenti and Alderman (2021) find that customers prefer to use digital platforms for simple transactional activities, while desiring high-touch interactions for more complex products and services, such as mortgages and financial advice. A survey finds that active advisory from lenders and interpersonal relationships with local brand representatives drive significantly higher mortgage borrower satisfaction (https://bankingjournal.aba.com/2024/11/survey-mortgage-lenders-helping-customers-navigate-tough-market-reap-benefits/).

[7]https://theuxda.com/blog/how-merger-acquisition-impacts-digital-customer-experience-in-banking

sufficient hard information to signal their quality. M&As-induced loan officer replacement or branch shutdown will lead to the loss of officers who possess such soft information. Allen et al. (2016) use bank M&As as an exogenous shock to bank-customer relationships, focusing on loss of soft information.

Recent cases support that lender M&As can disrupt lender-household relationships. 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 widely criticized for poor technological migration and inadequate customer communication. Customers reported difficulties using 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 failed to offer a solution. Two months after the integration, the number of complaints filed against Truist with the CFPB increased by more than 81%. Appendix A2 cites a complaint from an angry customer who decided to end a 38-year banking relationship with SunTrust due to the frustrating experience. 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. [8]

To qualify as an exogenous shock to lender-household relationships, lender M&As must be independent of other factors that might influence household refinancing, including local economic conditions and refinance contracts offered to households, conditional on the matched sample. While lender M&As and local economic conditions might be correlated, for example if the local area is a major market for the lender, conditional on a sample matched on county, the M&As are plausibly exogenous. The second concern is whether lender M&As would impact the refinance contracts offered to households. For example, 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 of-

[8] https://www.wsj.com/finance/banking/they-were-used-to-five-star-service-at-first-republic-now-theyre-just-regular-customers-a128e453

ferings. The sample matched on county ensures that treated and control households are exposed to the same competitive environment. Another possibility is that M&As may affect the acquiring lenders' loan offerings to customers. For example, the acquiring lenders may change their loan approval criteria or contract terms after the M&As. 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 loan offers after the M&As.

3.1.2 Results

Using the matched sample, I estimate specification 1. The dependent variable $IfRefi_{i,t}$ takes 1 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 times 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.

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

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 the five years since the shock, and shows a slow reversal. 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 $\mathbf{1}(Post)_t$.

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

Table 2 column (1) reports the average effect. On average, the treated household's refinancing probability decreases by 0.0069. Compared to the average refinancing rate of control households in the post-event period, which is 0.0099, this represents a 69.45% decline. An important question is whether this large drop stems from failing to refinance with the relationship lenders, or from failing to refinance with new lenders. To investigate this, I decompose the overall refinancing probability into two components: refinancing with the relationship lender and refinancing with new lenders, respectively. The dependent variable in column (2) takes 1 if household i refinances with relationship lenders in year t, and the dependent variable in column (3) takes 1 if household i refinances with new lenders in year t. The treated household's probability to refinance with the relationship lender decreases by 0.0039, which represents a 93.24% decline compared to 0.0042 for control households in the post-event period. The probability of refinancing with a new lender decreases by 0.0030, which represents a 51.91% decline compared to 0.0057 for control households in the post-event period. The results suggest that the disruption of lender-household relationships not only reduces the probability of refinancing with the relationship lender—mechanistically, as the lender was taken over and ceased to operate—but also lowers the probability of refinancing with new lenders. In other words, rather than switching to new lenders, the probability that household refinance with new lenders also declines.

I next address the concern that lender M&As may reduce household refinancing probability because the acquiring lenders offer less favorable contracts post M&As, rather than due to a disruption of lender-household relationships. First, I argue that this possibility is strongly rejected by the results. If the acquiring lenders offered less favorable loan contracts after the M&As, borrowers should be more likely to refinance with new lenders, or at least maintain the same likelihood of doing so. However, the fact that the shock reduces the probability of 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 were reported in Appendix A3, confirming the robustness of the main findings.

3.2 Refinance Loan Costs and Performance

This section studies, conditional on the refinance loans, if lender-household relationships affect the refinance loan characteristics, including loan costs and loan performance.

3.2.1 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 refinance loans of households whose relationship lender was acquired, with the M&A year designated as event year zero. To accurately capture interest rate changes at refinancing, I restrict the treated loans to fixed-rate refinance loans whose corresponding previous loans are also fixed-rate. 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 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 to treated loans based on the year, property county, and the term and type of the treated loan. Second, among these exact matches, I apply propensity score matching based on the loan amount and borrower income of the refinance loans, as well as the amount and interest rate 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.

3.2.2 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 $\mathbf{1}(Treated)_f$.[9] 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 $\mathbf{1}(Post)_t$.

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

Loan Costs

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

Taking the interest rate as the dependent variable, Figure 2(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 3 column (1) reports the corresponding average effect, which is statistically insignificant and economically small. Similarly, taking total loan costs as the dependent variable, Figure 2(b) and Table 3 column (2) 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 market power to charge a markup. Potentially it is because the U.S. mortgage market features highly standardized interest rate setting and a competitive environment (D. W. Berger et al., 2024).

Loan Performances

I further examine whether the loan performance of the treated and control loans differs. The dependent variable *Loan Delinquent* equals one if the loan was ever 90 or more days delinquent on monthly payments. The dependent variable *Loan Delinquent in Short Term* equals one if the loan became 90 or more days delinquent within the first three years after origination. Figure 3 plots the coefficients from the estimation of specification 3. Table 4 reports the coefficients from the estimation of specification 4. Again, the differences between the treated and control loans are statistically insignificant and economically small. The results show that the treated refinance loans exhibit similar quality to the control loans, and suggest that the disruption of lender-household relationships does not affect the lenders' screening standards on applications.

3.3 Channels

The results demonstrate that maintaining lender-household relationships helps households refinance in improving refinancing probability, without changes in refinancing costs or screening standards. What is the channel through which relationship lenders help household mortgage refinancing? Three potential channels include: providing information on potential refinancing opportunities, offering refinancing cost advantages, and utilizing soft information about borrower quality.

Informing channel Relationship lenders can inform borrowers of potential refinancing opportunities. [10] Lenders actively communicate with their relationship customers about potential refinancing opportunities in order to earn loan origination fees and maintain customer relationships. This communication has two important features: it is frequent, and it is trusted by borrowers, both of which are crucial for household refinancing decisions. Andersen et al. (2020) find inattention is one of the reasons why households fail to react to low interest rates. Byrne et al. (2023) conduct a field experiment in Ireland in which customers were mailed information about refinancing opportunities. They find that while different mail designs only produce small improvements, simply sending a reminder letter increases refinancing probability by 76%, highlighting a large reminder effect in reducing attention frictions. Furthermore, customers are cautious about refinancing opportunities. 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". The communication from relationship lenders helps mitigate both issues: It is frequent and serves as a reminder, and it is trusted by borrowers, making it particularly helpful in informing households about refinancing opportunities. The informing channel discussed here

[10] The information could refer either to introducing the concept of refinancing to households with little prior experience, or to informing customers who are already aware of refinancing but inattentive to favorable timing, such as periods of low interest rates. In this paper, I do not distinguish between these two types of information.

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.

Cost Advantage Channel Relationship lenders might help household refinancing by reducing refinancing costs. Buchak et al. (2023) argue that certain lenders have a cost advantage in refinancing their servicing customers, which can reduce customers' refinancing fees and improve refinancing probability. **Soft Information Channel** Relationship lenders might possess soft information about borrower quality, and the literature shows that the soft information is important in both household and corporate financing (Allen et al. (2016), A. N. Berger et al. (2024)).

The evidence that disruptions in lender-household relationships generate a large negative spillover effect on household refinancing probability with new lenders is consistent with the informing channel: after the relationship breaks, households are less likely to be aware of potential refinancing opportunities and therefore less likely to refinance, regardless of with relationship lenders or new lenders. In contrast, the cost advantage channel predicts that if households lose access to a low-cost refinancing opportunity, they should switch to the next best refinancing opportunity, meaning they would be more likely to refinance with new lenders, or at least the probability would remain unchanged. This prediction is inconsistent with the empirical evidence. Similarly, the soft information channel predicts that if the loss of soft information makes them can no longer secure refinancing with the relationship lender, they would switch to other lenders. However, the empirical evidence strongly rejects this prediction as well.

Moreover, the results on loan costs and performance also fail to support the alternative channels. The cost advantage hypothesis argues that lower refinancing costs increase the household refinancing probability. However, I find no evidence of cost changes. The soft information channel would predict that, following a relationship disruption, only households with sufficient hard information can refinance and thus should exhibit better loan performance. This pattern is not observed in the results.

A subsample test by borrower income further reinforces this conclusion. The cost advantage channel, if it exists, predicts that the disruption of relationships generates more negative results for households that are more sensitive to costs. Similarly, the soft information channel predicts that the disruption of relationships generates more negative results for households who rely more on soft information. Low-income households, compared 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 5 splits the full sample into high- and low-income groups based on the treated households' incomes at the origination of the loan outstanding in event year -1. There are no significant differences between the two groups, failing to support either the cost advantage channel or the soft information channel.

Overall, the results are consistent with the informing channel, rather than the cost advantage or soft information channels.

Extensions

I present extensional evidence on how the effect varies with loan characteristics or household demographics. The informing channel predicts that the relationship disruption should generate more negative effects for inattentive households, but weaker effects for households with stronger incentives to monitor refinancing opportunities on their own. For example, households seeking to extract home equity or those burdened with high existing interest rates are more likely to actively monitor refinancing options rather than depend on lenders' information. Table 6 tests the first prediction. It decomposes the overall refinancing probability into two components: refinancing at a lower interest rate (compared to the previous loan) and refinancing at a higher interest rate (compared to the previous loan), where the latter is typically associated with active purposes such as extracting home equity. The estimation follows specification 2. The results are consistent with the predication, showing that the relationship disruption shock does not affect refinancing activities motivated by such active purposes. Table 7 tests the second prediction, splitting the matched sample into high- and low-interest-rate groups based on the interest rates of the outstanding loans held by treated households in event year -1. Consistent with the prediction, the relationship disruption shock has a much smaller impact on households facing high existing interest rates.

Appendix A4 reports the cross-household demographics differences: households that are younger, with college education, and working in the finance industry rely less on the relationship lenders for refinancing. However, as the demographics data are a cross-sectional snapshot, I interpret it only as suggestive evidence.

4 A Structural Model of Lender Relationships and Household Refinancing

Previous empirical evidence shows that relationship lenders help households refinance by providing information about potential refinancing opportunities. While the results are well identified, several important but underexplored questions remain. First, this paper highlights a novel informing channel through which relationship lenders influence household refinancing, and prior literature largely focus on soft information or cost channels. A structural model that jointly incorporates these channels would allow for comparisons of their relative importance, and provide a more comprehensive understanding of the overall role of lender-household relationships. Second, refinancing is inherently a dynamic decision-making problem. The reduced-form evidence identifies effects from cross-sectional shocks. A structural model that explicitly incorporates the dynamic nature of refinancing decisions can shed light on how household behaviors are impacted in an intertemporal context. Lastly, refinancing is a key tool for household debt management and a central channel for monetary policy transmission. 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. Structural counterfactual analysis is therefore essential for evaluating the impacts of these policies on household refinancing.

Motivated by these considerations, this section develops a structural model of how lender-household relationships affect household mortgage refinancing. The first part presents the model. The second part describes the estimation sample. The third part discusses the estimation results. The last part conducts counterfactual analyses of potential policy designs.

4.1 Model

Following Andersen et al. (2020), I use a mixture model for household refinancing decisions. In each period, households go through two stages. In the first stage, each household enters one of two states: "awake" or "asleep". In the second stage, awake households choose which lender to refinance with, or choose not to refinance. Asleep households refinance with zero probability. The market conditions and lender characteristics are assumed to be exogenous to a household's refinancing decision, a common simplifying assumption in the literature estimating individual-level demand (Seiler, 2013).

Central to the model is that lender-household relationships enter both stages: The relationships enter the first stage, impacting household awake probability. This captures the idea that relationship lenders provide information to the household, thereby influencing the household's probability of being attentive to potential refinancing opportunities. The relationships enter the second stage, impacting the utility that the household gets when refinancing with a particular lender. This reflects the idea that relationship lenders provide "value" (e.g., cost or soft information advantages/disadvantages) to the household and thus influence the household's choice of lender.

First Stage

In the first stage of period t, each household i enters one of two states: "awake" with probability $1 - w_{it}$, or "asleep" with probability w_{it}. The probability that a household is asleep is modeled in equation 5. A relationship lender is defined as the originator of the outstanding mortgage, and $k_{i,t-1}$ is the relationship lender of household i by the end of last period $t-1$. $z_{ik_{i,t-1}t-1}$ are characteristics of household i's relationship with her relationship lender $k_{i,t-1}$ by the end of last period $t-1$. The characteristics include the relationship duration and lender attributes such as type and size, which will be described in detail in the estimation section.

$$w_{it}(\chi) = \frac{\exp(\chi' z_{ik_{i,t-1}t-1})}{1 + \exp(\chi' z_{ik_{i,t-1}t-1})} \tag{5}$$

The first stage captures the idea that lender-household relationships can provide information to the household, thereby influencing the probability that the household becomes attentive to refinancing opportunities, and proceeds to the second stage to make a refinancing decision.

Second Stage

In the second stage of period t, asleep households refinance with zero probability. Awake households choose to refinance with lender j from a set of lenders $\{J_{it}\}$ (Consideration Set), or to not refinance (choose the outside option 0). For the awake household i, the indirect utility of refinancing with lender j in period t is given by equation 6. I_{ijt} is the refinancing incentive, and I assume ϵ_{ijt} is a mean zero stochastic term distributed independent and identically distributed (i.i.d.) type I extreme value across households, lenders and periods.

$$u_{ijt} = e^{\beta} I_{ijt} + \epsilon_{ijt} \tag{6}$$

Following simplifying assumptions in the literature modeling individual-level refinancing behavior (Andersen et al., 2020, Fisher et al., 2024), I assume that all households refinance from a fixed-rate mortgage to another fixed-rate mortgage, without changing the loan term or principal amount, and the interest rate for the new mortgage is set at the prevailing market level. Any deviations from the market rate that are specific to a lender are captured through additional costs, which are part of parameters to be estimated. The refinancing incentive I_{ijt} is formally given in equation 7. The incentive is the difference between the existing mortgage interest rate r_{it}^{old} that the household is paying and the interest rate on a new mortgage r_t^{new}, which is the prevailing market interest rate, less a threshold O_{ijt}. Intuitively, a positive incentive indicates that the interest rate reduction is sufficiently large, such that the savings in mortgage payments exceed the threshold.

$$I_{ijt} = (r_{it}^{old} - r_t^{new}) - O_{ijt} \tag{7}$$

To measure O_{ijt}, I adapt the closed-form solution developed by Agarwal et al. (2013) (ADL). The ADL model assumes that mortgages have an infinite maturity with principal declining at an exogenous constant rate, that mortgages may be refinanced multiple times, that mortgage borrowers are risk-neutral with respect to refinancing proceeds, and that the mortgage interest rate follows an arithmetic random walk. The ADL closed-form threshold has been used as a benchmark for both empirical analysis (Keys et al., 2016) and structural estimation (Andersen et al., 2020) in the household refinancing literature. This paper modifies the ADL solution, and the modified refinancing threshold O_{ijt} is given by equations 8.

$$O_{ijt} = \frac{1}{\psi_{it}} \left[\phi_{it} + W\left(-\exp(-\phi_{ijt})\right)\right], \tag{8}$$

$$\psi_{it} = \frac{\sqrt{2(\rho+\lambda_{it})}}{\sigma}, \tag{9}$$

$$\phi_{ijt} = 1 + \psi_{it}(\rho+\lambda_{it})\frac{\kappa_{ijt}}{m_{it}(1-\tau)} \tag{10}$$

$W()$ denotes the Lambert W-function, ρ is the discount rate, σ is the volatility of the annual change in the interest rate, τ is the marginal tax rate, λ_{it} is the expected real rate of exogenous mortgage repayment, κ_{ijt} is the refinancing cost when refinancing with specific lender j, and m_{it} is the remaining mortgage principal. ρ and τ are calibrated using the recommended parameters in ADL, with $\rho = 0.05$ and $\tau = 0.28$. σ is calibrated using the annualized standard deviation of the Freddie Mac 30-year mortgage rate from April 1971 to December 2023.

λ_{it} is specified in equation 11. In this equation, μ_{it} is the annual probability of household moving, calibrated to 0.1. T_{it} is the remaining term of the mortgage in years. π_t is the inflation rate, calibrated to the realized consumer price inflation over the past year.

$$\lambda_{it} = \mu_{it} + \frac{r_{it}^{old}}{\exp[r_{it}^{old}T_{it}]-1} + \pi_t \tag{11}$$

κ_{ijt} is the refinancing cost when household i refinances with lender j in period t, and it is modeled in equation 12. It consists of baseline costs $2000 + 0.01 * m_{it}$ and additional costs $exp[\phi + 1(j = k_{it-1})\phi_{rl}' z_{ik_{i,t-1}t-1}]$. The baseline costs capture the monetary refinancing costs and are assumed to be 1% of mortgage amount plus \$2,000. The additional costs capture the psychological costs and the relationship lender specific costs. A constant ϕ captures a psychological component as suggested by Andersen et al. (2020). If the household refinances with its previous-period relationship lender k_{it-1}, the relationship lender specific costs $\phi_{rl}' z_{ik_{i,t-1}t-1}$ are included, in which $z_{ik_{i,t-1}t-1}$ are characteristics of household i's relationship with its relationship lender $k_{i,t-1}$ in period $t-1$, the same set of characteristics considered in the first stage. This relationship lender specific costs generally captures the idea that relationship lenders provide "value" to the household, and therefore influence the household's decision of which lender to choose. For example, a negative value of $\phi_{rl}' z_{ik_{i,t-1}t-1}$ implies that refinancing with the last-period relationship lender incurs lower costs relative to non-relationship lenders. This may reflect lower fees or interest rates, lower search costs, reduced application costs due to soft information, or a behavioral preference for familiar institutions. Because this paper aims to distinguish the informational role of relationships (first stage) from their impacts on utility (second stage), all utility-relevant components are consolidated within this additional cost term.

$$\kappa_{ijt} = 2000 + 0.01 * m_{it} + exp[\phi + 1(j = k_{it-1})\phi_{rl}' z_{ik_{i,t-1}t-1}] \tag{12}$$

Given the utility specified in equation 6, the probability that an awake household i refinances with lender j at time t can be written as:

$$P_{it}(Refinance\ with\ lender\ j) = \frac{exp(u_{ijt})}{\sum_{l \in \{J\} \cup 0} exp(u_{ilt})} \tag{13}$$

The utility from choosing not to refinance is normalized to zero. I additionally assume the consideration set includes the last-period relationship lender and n_{it} non-relationship lenders. That is, $\{J_{it}\} = \{k_{it-1}\} \cup \{j_{i1}, \ldots, j_{in_{it}}\}, n_{it} \geq 1$. Denote the household-level outcomes by y_{iRt} and y_{iNRt}. y_{iRt} takes one if household i refinances with her last-period relationship lender k_{it-1} at time t. y_{iNRt} takes one if household i refinances with a lender other than her previous relationship lender at time t. This specification implies the likelihood function of each awake household as in equation 14, in which $u_{ik_{it-1}t}(\beta, \phi, \phi_{rl})$ is the utility from refinancing with the last-period relationship lender, $u_{ij_{\neq k}t}(\beta, \phi)$ is the utility from refinancing with a non-relationship lender.

$$\begin{aligned} L_{it}^{awake}(\beta, \phi, \phi_{rl}) = (1 - y_{iRt} - y_{iNRt}) & \frac{1}{1 + exp(u_{ik_{it-1}t}) + n_{it}exp(u_{ij_{\neq k}t})} \\ + y_{iRt} & \frac{exp(u_{ik_{it-1}t})}{1 + exp(u_{ik_{it-1}t}) + n_{it}exp(u_{ij_{\neq k}t})} \\ + y_{iNRt} & \frac{n_{it}exp(u_{ij_{\neq k}t})}{1 + exp(u_{ik_{it-1}t}) + n_{it}exp(u_{ij_{\neq k}t})} \end{aligned} \tag{14}$$

Likelihood Function

Combining equations 5 and 14, the likelihood function for household i is:

$$L_{it} = (1 - w_{it}(\chi))L_{it}^{awake} + w_{it}(\chi)L_{it}^{asleep} \tag{15}$$

The corresponding log-likelihood function over the full sample is:

$$lnL = \sum_t \sum_i ln(L_{it}) \tag{16}$$

Identification

The parameters to be estimated include the vector χ, the scalars β and ϕ, and the vector ϕ_{rl}. χ captures how the lender-household relationship affects the household's probability of becoming attentive ("awake") and thus considering refinancing. ϕ captures psychological costs associated with refinancing. ϕ_{rl} captures relationship-lender-specific costs, reflecting the idea that relationship lenders provide "value" to households and thereby influence their lender choice. β 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 with highly positive incentives. The relative probability of refinancing with a relationship lender versus a non-relationship lender, together with the overall refinancing probability, jointly identifies ϕ and ϕ_{rl}. β is identified from the slope of the refinancing probability with respect to the incentive I.

4.2 Estimation Sample

This section describes the estimation sample and the construction of variables.

To construct the estimation sample, I begin by applying filters to household-year observations. I keep observations that have outstanding 30-year fixed-rate conventional mortgages by the end of the previous year. I exclude observations with missing values in any variables used in the estimation, as well as households whose relationship lenders were acquired by the end of the previous year.

The refinancing probability is key to parameter estimation. In the full HMDA-VERISK household-year sample, the average refinancing probability is 5.0%, which is close to the national average of 7.7% from 2014 to 2023 estimated using the National Mortgage Database (NMDB). However, as this model aims to estimate the refinancing costs with relationship versus non-relationship lenders, the refinance loans with missing relationship lender information are excluded. This step substantially reduces the sample mean of refinancing probability, which is unsurprising given that Verisk reports only up to the three most recent loans and refinancing events are relatively rare. The resulting underestimated refinancing probability is not a concern for the empirical analysis, as long as the exogenous shocks to relationships are independent of the data missingness pattern. It is highly plausible, given that the shocks occur at the lender level, and treated and control households are matched based on their pre-shock refinancing histories. However, it poses a concern for the structural estimation. Intuitively, the underestimated refinancing probability may lead to an overestimation of refinancing costs or the probability of inattention. [11]

Therefore, I further rebalance the sample such that the sample average refinancing probability matches the refinancing rate estimated using the NMDB. The NMDB, published by Federal Housing Finance Agency (FHFA) and the CFPB, reports the national number of outstanding single-family mortgage loans since 2013, as well as the national number of refinance loan originations. The refinancing rate each year is calculated as national number of refinance loan originations divided by the national number of outstanding loans at the end of the previous year. Appendix A5 reports the refinancing rate estimated using the NMDB from 2014 to 2023. In each year from 2014 to 2023, I keep all household-year observations with a refinancing event, and then randomly draw household-year observations without refinancing such that the average refinancing probability in the rebalanced sample matches the refinancing rate estimated using the NMDB. This procedure is consistent with the assumption that refinancing utility residuals are i.i.d. across households and lenders. Observations before 2014 are excluded.

The prevailing market interest rate r_t^{new} is measured by the average interest rate for a 30-year fixed-rate mortgage from Freddie Mac's Primary Mortgage Market Survey (PMMS). The number of non-relationship lenders in a household's consideration set n_{it} is proxied by the number of non-relationship lenders whose mortgage origination share in the household's county of residence exceeded 10% in the previous year, or one, whichever is larger. This assumes households consider their relationship lender along with other lenders that dominate the local mortgage market. Unsurprisingly, the number of dominant lenders is generally small due to the competitive nature of the mortgage market. While this number appears small, it is consistent with survey evidence showing that most households do not engage in extensive lender shopping and typically consider only two or three lenders.

The model also allows lender-household relationships to vary with certain characteristics.

[11] The ratio of refinancing with relationship lenders to non-relationship lenders is key to identifying the relationship-lender-specific costs. Since Verisk collects data from County Recorder and County Assessor Offices, it is unlikely that the Verisk sample is biased toward refinancing with any particular type of lender.

In particular, $z_{ik_{i,t-1}t-1}$ are characteristics of household i's relationship with her relationship lender $k_{i,t-1}$ by the end of the previous year $t-1$. The characteristics considered include the relationship duration, lender type and size. All relationship-related variables are measured as of year $t-1$ to ensure that they reflect the characteristics observed before the household receives information and makes refinancing decisions. Relationship duration captures the idea that trust and familiarity with the lender are typically built over time. Duration is calculated as the difference between the previous year and the year in which the relationship was established, plus one. The duration is coded into indicator variables. The reference category is a one-year relationship. The included dummies represent durations of 2–5 years, 6–10 years, 11–15 years, and 16 years or more. Lenders of different types vary in their communication approaches and pricing strategies. For example, large banks often rely on local branches, whereas mortgage companies tend to outperform in online marketing. Buchak et al. (2023) document that fintech lenders can reach relationship borrowers more effectively but charge higher fees. Lenders are grouped into the following categories based on the NIC classification: National Bank (NAT, the reference category), Domestic Entity Other(DEO, including mortgage companies such as Rocket Mortgage, LLC), Credit Union (CU, including State Credit Union and Federal Credit Union), and State-Chartered Bank (SCB, including State Member Bank and Non-member Bank), and all other lenders. Previous literature also suggests that lenders of different sizes may differ in their communication and pricing behavior. I proxy size by the lender's share of U.S. mortgage originations in the previous year, calculated based on the HMDA data. Table 8 presents the summary statistics of the estimation sample.

4.3 Estimation Results

The parameters are estimated using maximum likelihood estimation (MLE). Table 9 presents the estimation results. Model 1 includes only constant terms for χ, β, ϕ and ϕ_{rl}. Model 2 through 4 explore the importance of the lender-household relationships. Model 2 adds the relationship duration to both χ and ϕ_{rl}. Model 3 adds the relationship lender's type. Model 4 adds the relationship lender's market share. Model 5 incorporates all relationship characteristics and will be the benchmark specification for the main analysis.

Relationship Duration

Figure 4(a) plots how the awake probability varies with relationship duration. A reference household, which is a household in a one-year relationship with a national bank of median market share, has an awake probability of 8.98%. [12] As the relationship extends to 2–5 years, the awake probability more than doubles to 19.88%, and remains above 20% for longer durations. The results suggest that longer lender-household relationships substantially improve the probability that households become attentive to refinancing opportunities, and that this attentiveness persists. This may reflect growing customer trust and familiarity with the lender over time.

Figure 4(b) plots how the additional refinancing costs ($e^{\phi+\phi_{rl}}$) vary with the relationship duration. The estimated costs for the reference household to refinance with its relationship lender are $2,252, which is 43% lower than the estimated costs of refinancing with a non-relationship lender ($3,957). This suggests that relationships reduce refinancing costs in the early stages. The cost advantage follows a U-shaped pattern over the relationship duration. As the relationship extends, the cost savings increase and peak at 6-10 years, with costs as low as $898. After that, the advantage diminishes and eventually reverses. For relationships lasting 16 years or longer, the refinancing costs with the relationship lender rise to $5,941, which is 50% higher than that with a non-relationship lender. This pattern suggests that relationship lenders offer favorable terms early on to build customer loyalty, but may exploit that loyalty and charge a markup once the relationship is well established.

Relationship Lender's Type

Figure 4(c) plots how the awake probability varies across the relationship lender types. For a reference household in relationship with a national bank, the awake probability is

[12] For comparison, Andersen et al. (2020) report awake probabilities in the Danish mortgage market ranging from 4% to 16%.

8.98%. For households whose relationship lender is classified as "domestic entity other", such as mortgage companies, the awake probability is 16.33%, an 82% increase over the reference. This suggests that mortgage companies may employ more effective communication or marketing strategies than traditional national banks. Credit unions also exhibit high informing abilities. Their relationship borrowers have an awake probability of 14.29%, 59% higher than the reference. This is consistent with their reputation for personalized service and member-focused communication. State-chartered banks yield a slightly higher awake probability of 10.35% than the reference. Although the magnitude is smaller, the difference is statistically significant. It aligns with the view that local lenders often maintain better relationships with borrowers. Overall, the results highlight heterogeneity in the informing ability across lender types. Mortgage companies and credit unions outperform national banks and state-chartered banks in engaging their borrowers.

Figure 4(d) illustrates how the additional refinancing costs vary by relationship lender type. For a reference household in relationship with a national bank, the additional cost is \$2,252. In contrast, households in relationship with a mortgage company face much higher costs of \$27,230, which is 1109% higher than that for the reference household. This substantial difference suggests that mortgage companies have a greater ability to extract surplus from their relationship borrowers, potentially due to stronger customer loyalty. State-chartered banks charge slightly higher costs of \$2,610 compared to the reference. Credit Unions charge almost zero additional costs. This pattern is consistent with their not-for-profit nature. Notably, the cost advantage of Credit Unions is large enough to offset the household-level psychological cost component ϕ. It is plausible that Credit Unions provide subsidies to support their members during refinancing. These findings reveal heterogeneity in the pricing strategies across lender types. Borrowers in relationships with mortgage companies face significantly higher costs, while those in relationships with Credit Unions benefit from minimal refinancing costs.

Relationship Lender's Market Share

Figure 4(e) shows that the relationship lender's market share is negatively correlated with the household's awake probability. This finding is consistent with the literature that smaller lenders outperform in maintaining customer relationships. The magnitude of the effect is modest. For a reference household in a one-year relationship with a national bank, the awake probability is 9.08% at the 10th percentile of lender market share, which is 14% higher than the 7.98% at the 90th percentile.

Figure 4(f) shows that the relationship lender's market share is negatively correlated with the additional refinancing costs. The magnitude of this effect is more pronounced than its impact on the awake probability. For a reference household in a one-year relationship with a national bank, the estimated additional cost is $2,388 at the 10th percentile of lender market share, which is 91% higher than the $1,247 at the 90th percentile.

In summary, the lender-household relationships substantially affect both the likelihood of households becoming attentive to refinancing opportunities and the refinancing costs they face. Relationships of longer duration and relationships with mortgage companies or credit unions increase the probability that households become attentive. This suggests that trust, familiarity, and lender communication play important roles in prompting household refinancing. In contrast, the refinancing costs follow a U-shaped pattern over relationship duration: households enjoy lower costs in early to mid-stage relationships, but face higher costs in longer relationships. Mortgage companies charge markedly higher costs to their relationship borrowers, while credit unions charge minimal additional costs.

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 explores two lender-targeted policies aimed at promoting household refinancing. The first policy focuses on increasing attentiveness: specifically, it raises all households' awake probability to the level observed in relationships with mortgage companies, the highest among all lender types. The second policy targets refinancing costs: it lowers the additional refinancing costs to the level observed in relationships with national banks, the lowest among all lender types except credit unions. For simplicity, all lender characteristics are held constant except the one targeted by the policy.

Figure 5 plots the results. The baseline model without policy interventions reports an average refinancing probability of 3.43% over the full sample. Under the "Improve Awake" policy, the refinancing probability increases to 4.25%, a 24% increase compared with the baseline model. Under the "Reduce Cost" policy, the refinancing probability rises to 4.08%, representing a 19% increase. When both policies are implemented together, the refinancing probability reaches 4.91%, yielding a 43% increase. In most years, the "Improve Awake" policy has a larger effect than the "Reduce Cost" policy. An exception is in year 2023, when high interest rates made costs the main barrier against refinancing rather than inattention. On average, improving awake probability is more powerful in increasing refinancing rates than reducing refinancing costs. This is consistent with literature highlighting inattention as a key obstacle to household refinancing. Moreover, compared with cost-based interventions that reduce lender revenues and might be difficult to enforce, improving awake probability is likely more feasible and cost-effective.

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 as inattentive as those in relationships with national banks, which rely on traditional communication channels and exhibit the lowest borrower awake probability among all lender types. Figure 6 plots the results. Under this policy, the average refinancing probability declines to 2.53%, representing a 26% decrease compared to the baseline result. This substantial reduction raises important questions about whether marketing restrictions should be tailored differently in the mortgage refinancing sector.

5 Conclusion

This paper investigates the role of lenders in shaping household refinancing behavior, using a unique dataset tracking lender-household relationships across approximately 25 million mortgage loans. The analysis shows that when lender-household relationships are disrupted by exogenous shocks, households are significantly less likely to refinance, with an overall decline of 69.45%. Specifically, refinancing with the original relationship lender declines by 93.24%, and refinancing with new lenders declines by 51.91%. Conditional on completing a refinance, however, the disruption does not materially affect the interest rate, fees, or subsequent loan performance. These results support the interpretation that relationship lenders play a key role by providing borrowers with timely and trusted information about refinancing opportunities.

This paper further develops a structural model in which relationships affect households' awareness of refinancing opportunities and refinancing costs simultaneously. The structural model estimation results demonstrate that lender-household relationships play a critical role in shaping the likelihood of households becoming attentive to refinancing opportunities, as well as the refinancing costs they face. The counterfactual analysis of lender-targeted policies provides insights for potential policy designs.

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Figures

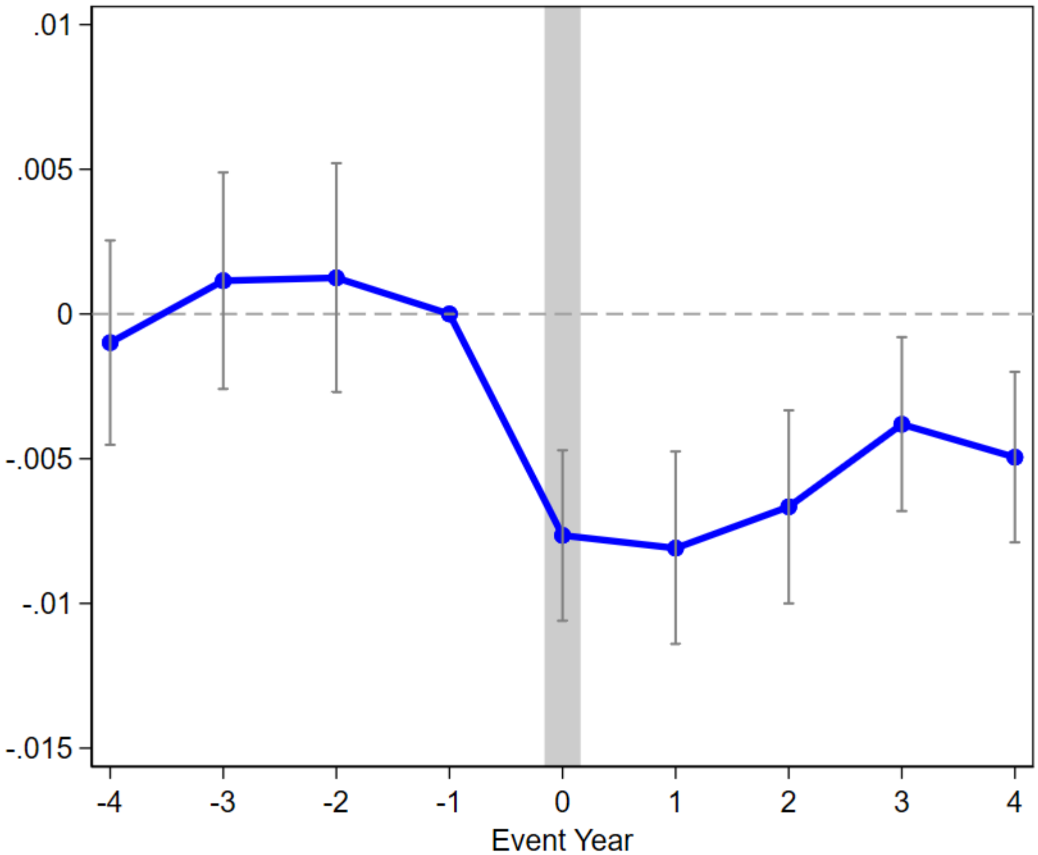
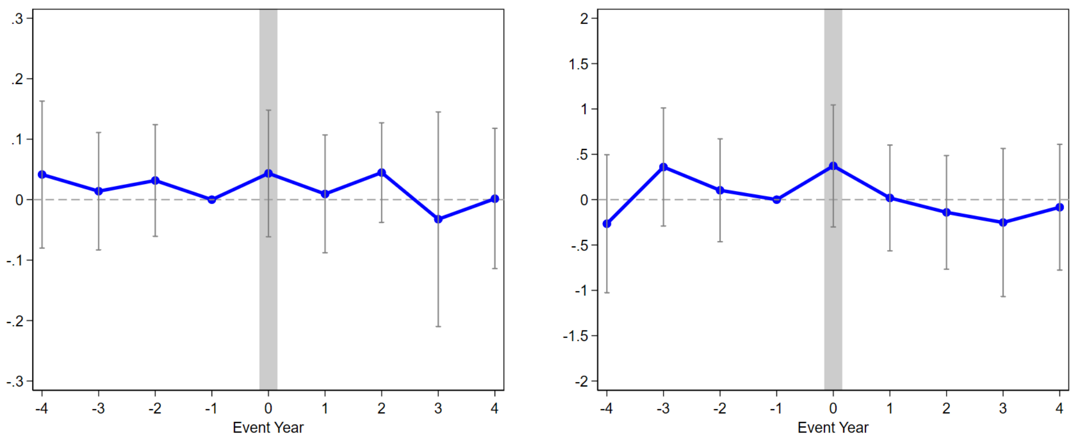


Figure 1: Mortgage Refinancing Probability

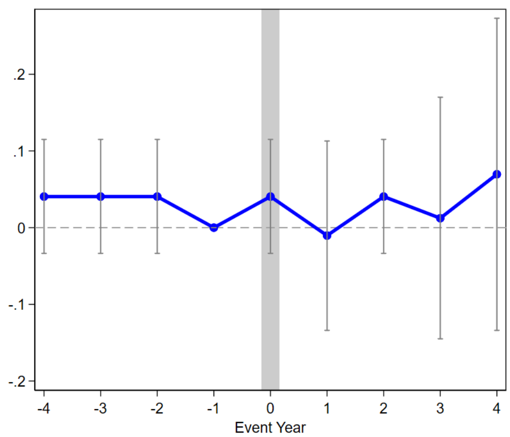
Note: This Figure plots the coefficients of $IfRefi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t=\delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable $IfRefi_{i,t}$ takes 1 if household i refinances in year t,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



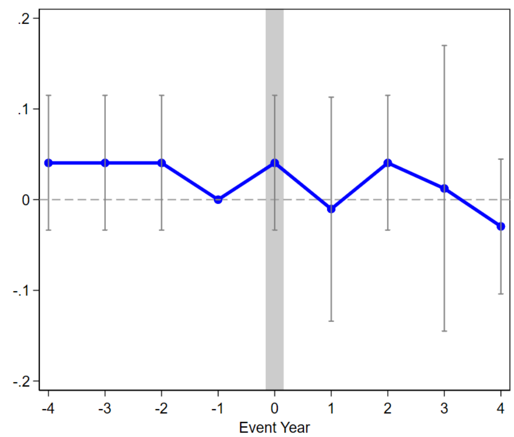
(a) Loan Interest Rate(%) (b) Total Loan Costs(k)

Figure 2: Refinanced Loan 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 refinancing 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 refinancing loans of households whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the incumbent mortgage. Each treated loan is matched to control loans, which are comparable refinancing loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a bank M&A shock.



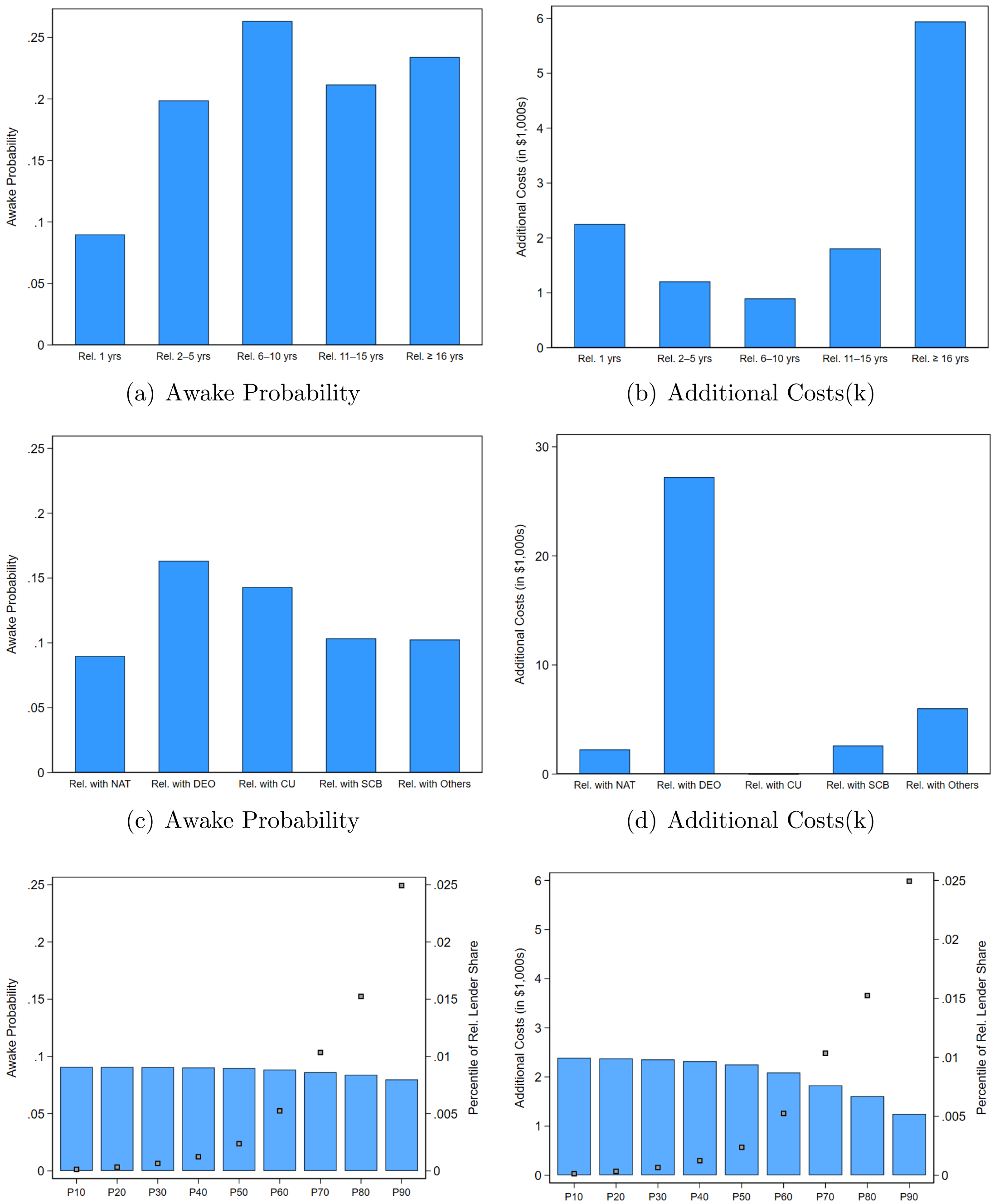
(a) Loan Delinquent



(b) Loan Delinquent in Short Term

Figure 3: Refinanced Loan Performance

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 *Loan Delinquent* equals one if the loan was ever 90 or more days delinquent on monthly payments. The dependent variable *Loan Delinquent in Short Term* equals one if the loan became 90 or more days delinquent within the first three years after origination. 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 refinancing loans of households whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the incumbent mortgage. Each treated loan is matched to control loans, which are comparable refinancing loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a bank M&A shock.



(a) Awake Probability

(b) Additional Costs(k)

(c) Awake Probability

(d) Additional Costs(k)

(e) Awake Probability

(f) Additional Costs(k)

Figure 4: Model Estimation

Note: This Figure plots the estimation results in Table 9 Model 5. (a), (c), (e) plots how the awake probability varies with relationship duration, relationship lender type, and relationship lender market share, respectively. (b), (d), (f) plots how the additional refinancing cost ($e^{\phi+\phi_{rl}}$) varies with relationship duration, relationship lender type, and relationship lender market share, respectively.

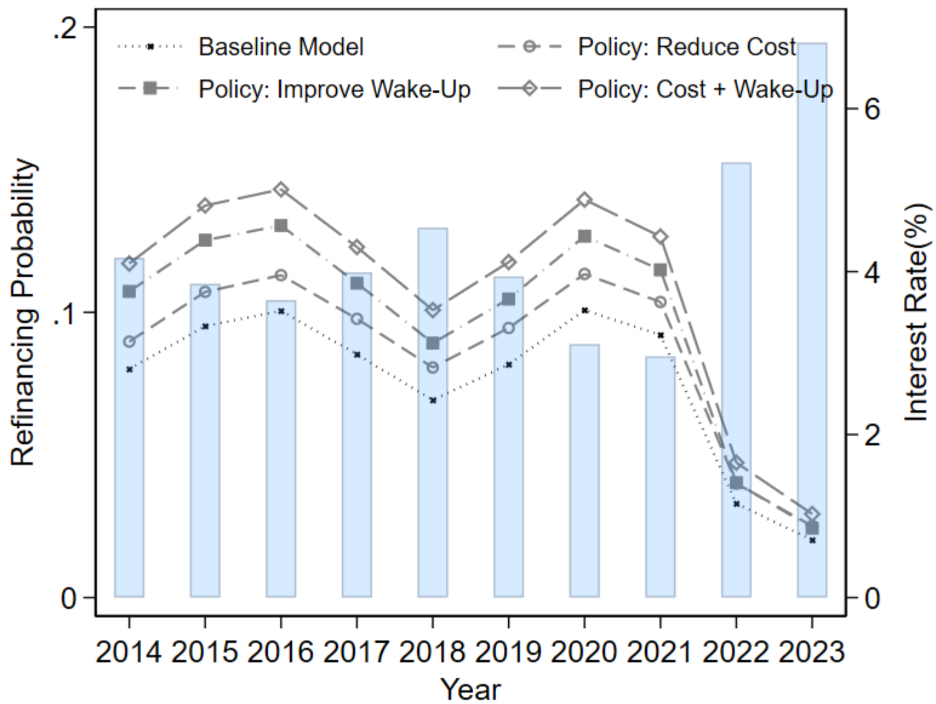


Figure 5: Policies Promoting Refinancing

Note: This Figure plots the counterfactual analysis of two policies by year. The first policy is to improve awake: it increases all households' awake probability to the level associated with DEO, the highest among all lenders. The second policy is to reduce cost: it lowers all households' additional refinancing cost to the level associated with national banks, the lowest among all lenders except credit unions.

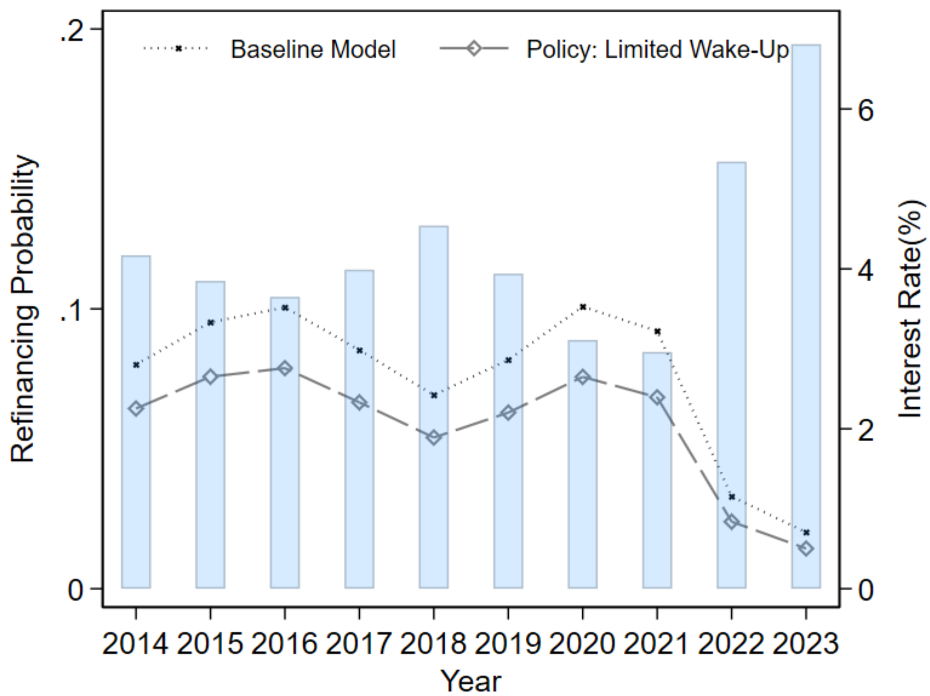


Figure 6: Policies Limiting Lenders' Reaching out

Note: This Figure plots the counterfactual analysis of a "Limit Reaching-Out" policy that reduces all households' awake probability to the level observed for national banks, the lowest awake probability among all lender types.

Table 1: HMDA-Verisk Summary Statistics

This table describes the summary statistics of the HMDA-Verisk data.

Panel A: All Loans				
	Mean	Median	SD	N
Loan Amount(k)	237.0346	196.0000	169.0186	24691164
Loan Term(year)	26.9440	30.0000	6.2647	23836858
Borrower Income(k)	106.7316	86.0000	75.1808	23226773
IfRefi	0.3597	0.0000	0.4799	24691164
IfRefi with Relationship Lender	0.0611	0.0000	0.2396	18101742
IfRefi with New Lender	0.0654	0.0000	0.2473	18101742
Interest Rate(%)	4.2189	3.7500	1.4698	12688935
Total Loan Costs(k)	5.3378	4.3661	3.7620	9297869
Loan Delinquent	0.0321	0.0000	0.1762	2960071
Loan Delinquent in Short Term	0.0190	0.0000	0.1367	2960071
Panel B: Refinanced Loans				
	Mean	Median	SD	N
Loan Amount(k)	220.9737	184.0000	152.2769	8880798
Loan Term(year)	24.6885	30.0000	7.3281	8593947
Borrower Income(k)	107.2760	89.0000	72.6392	7930198
IfRefi	1.0000	1.0000	0.0000	8880798
IfRefi with Relationship Lender	0.4830	0.0000	0.4997	2291376
IfRefi with New Lender	0.5170	1.0000	0.4997	2291376
Interest Rate(%)	3.8157	3.2300	1.4074	3653966
Total Loan Costs(k)	4.0739	3.3201	2.9628	2642927
Loan Delinquent	0.0296	0.0000	0.1696	1072007
Loan Delinquent in Short Term	0.0160	0.0000	0.1256	1072007

Table 2: Mortgage Refinancing Probability

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable in column (1) takes 1 if household i refinances in year t, the dependent variable in column (2) takes 1 if household i refinances with the relationship lender in year t, the dependent variable in column (3) takes 1 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated household is matched to control households located in the same county, holding comparable existing loans prior to the bank M&A shock, but never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	IfRefi	IfRefi with Relationship Lender	IfRefi with New Lender
Treated × Post	-0.0069***	-0.0039***	-0.0030***
	(-9.5984)	(-8.3918)	(-5.3853)
Household FE	YES	YES	YES
Event Year FE	YES	YES	YES
Observations	573162	573162	573162
R^2	0.135	0.147	0.131

Table 3: Refinanced Loan 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) is the loan interest rate, the dependent variable in column (2) 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 $\mathbf{1}(Post)_t$. The regression controls matched groups fixed effect, event year fixed effects, and the treatment status. Treated loans are refinancing loans of households whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated loan is matched to control loans, which are comparable refinancing loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the matched group level.* <0.1 ** <0.05 *** <0.01.

	Interest Rate(%)	Total Loan Costs(k)
Treated × Post	0.0011	-0.1097
	(0.0408)	(-0.7278)
Matched Group FE	YES	YES
Event Year FE	YES	YES
Treated	YES	YES
Observations	8028	5168
R^2	0.860	0.379

Table 4: Refinanced Loan Performance

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) equals one if the loan was ever 90 or more days delinquent on monthly payments. The dependent variable in column (2) equals one if the loan became 90 or more days delinquent within the first three years after origination. 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 $\mathbf{1}(Post)_t$. The regression controls matched groups fixed effect, event year fixed effects, and the treatment status. Treated loans are refinancing loans of households whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated loan is matched to control loans, which are comparable refinancing loans of households located in the same county, holding comparable loans before refinancing, but who never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the matched group level.* <0.1 ** <0.05 *** <0.01.

	Loan Delinquent	Loan Delinquent in Short Term
Treated × Post	0.0106	-0.0009
	(0.3548)	(-0.0326)
Matched Group FE	YES	YES
Event Year FE	YES	YES
Treated	YES	YES
Observations	667	667
R^2	0.538	0.457

Table 5: Mortgage Refinancing Probability by Borrower Income

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using subsamples of matched sample. The matched sample is splited into high/low income groups based on the treated household's income at origination of their existing loan at event year -1. Column (1) reports results using low income subsample, and column (1) reports results using high income subsample. The dependent variable takes 1 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated household is matched to control households located in the same county, holding comparable existing loans prior to the bank M&A shock, but never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	Low Income Household	High Income Household
Treated × Post	-0.0058***	-0.0082***
	(-6.6814)	(-6.9188)
Household FE	YES	YES
Event Year FE	YES	YES
Observations	309114	264048
R^2	0.135	0.134
Differences	-0.0024	
	(-1.6223)	

Table 6: Refinancing with Lower Rate vs Higher Rate

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta\mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable in column (1) takes 1 if household i refinances at a lower interest rate (compared to previous loan) in year t, the dependent variable in column (2) takes 1 if household i refinances at a higher interest rate (compared to previous loan) 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated household is matched to control households located in the same county, holding comparable existing loans prior to the bank M&A shock, but never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	IfRefi with Lower Rate	IfRefi with Higher Rate
Treated × Post	-0.0012***	0.0002
	(-3.1119)	(0.8133)
Household FE	YES	YES
Event Year FE	YES	YES
Observations	573162	573162
R^2	0.133	0.125

Table 7: Mortgage Refinancing Probability by Existing Interest Rate

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta\mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using subsamples of matched sample. The matched sample is splited into high/low interest rate groups based on the interest rate of the existing loan of treated household at event year -1. Column (1) reports results using low interest rate subsample, and column (1) reports results using high interest rate subsample. The dependent variable takes 1 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated household is matched to control households located in the same county, holding comparable existing loans prior to the bank M&A shock, but never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	Low Existing Rate	High Existing Rate
Treated × Post	-0.0122***	-0.0016*
	(-11.0392)	(-1.7599)
Household FE	YES	YES
Event Year FE	YES	YES
Observations	285672	287490
R^2	0.140	0.130
Differences	0.0106***	
	(7.3749)	

Table 8: Summary Statistics of Structural Estimation Sample

This table describes the summary statistics of the Structural Estimation Sample.

	Mean	Median	SD	N
Households:				
IfRefi	0.0383	0.0000	0.1920	889889
IfRefi with Relationship Lender	0.0164	0.0000	0.1269	889889
IfRefi with New Lender	0.0220	0.0000	0.1466	889889
Incumbent Interest Rate(%)	3.7127	3.4500	0.9839	889889
Current Market Interest Rate(%)	5.9884	6.8100	1.2218	889889
Remaining Principal(million)	0.2688	0.2329	0.1633	889889
Remaining Loan Term(year)	27.2118	28.0000	2.3670	889889
Number of Non-Rel. Lenders	1.0876	1.0000	0.3151	889889
Last-Year Relationships:				
Rel. 2–5 yrs	0.5885	1.0000	0.4921	889889
Rel. 6–10 yrs	0.0868	0.0000	0.2816	889889
Rel. 11–15 yrs	0.0237	0.0000	0.1520	889889
Rel.$\geq$ 16 yrs	0.0061	0.0000	0.0775	889889
Rel. with DEO	0.5262	1.0000	0.4993	889889
Rel. with CU	0.0946	0.0000	0.2927	889889
Rel. with SCB	0.1262	0.0000	0.3321	889889
Rel. with Others	0.0364	0.0000	0.1874	889889
Rel. Market Share	0.0097	0.0024	0.0155	889889

Table 9: Model Estimation

This table reports the results of the structural estimation. Model 1 includes only constant terms for χ, β, ϕ and ϕ_{rl}. Model 2 through 4 explore the importance of lender-household relationship. Model 2 adds the relationship duration to both χ and ϕ_{rl}. Model 3 adds the relationship lender types. Model 4 adds the relationship lender's market share. Model 5 includes all relationship characteristics.

	Model 1	Model 2	Model 3	Model 4	Model 5
$\boldsymbol{\chi}$	1.5460***	2.1453***	1.6293***	1.5118***	2.3027***
	(109.0895)	(105.8047)	(84.9844)	(95.3455)	(85.4771)
Rel. 2–5 yrs		-0.9475***			-0.9224***
		(-42.3007)			(-44.3307)
Rel. 6–10 yrs		-1.2158***			-1.2874***
		(-42.5607)			(-47.2132)
Rel. 11–15 yrs		-0.8201***			-1.0015***
		(-18.0670)			(-21.7470)
Rel.$\geq$ 16 yrs		-0.8660***			-1.1307***
		(-8.9638)			(-10.5313)
Rel. with DEO			-0.4117***		-0.6820***
			(-18.8361)		(-28.2284)
Rel. with CU			-0.4659***		-0.5251***
			(-17.3156)		(-17.4601)
Rel. with SCB			-0.0793***		-0.1568***
			(-2.5876)		(-4.5499)
Rel. with Others			-0.1793***		-0.1468***
			(-3.7613)		(-2.6819)
Rel. Market Share				2.7986***	5.6992***
				(5.4671)	(10.0534)
$\boldsymbol{\beta}$	-0.5578***	-0.5583***	-0.6214***	-0.5541***	-0.5964***
	(-70.8088)	(-75.0151)	(-80.6854)	(-69.5742)	(-87.1973)
$\boldsymbol{\phi}$	0.1479	0.6053***	1.2626***	0.1523	1.3755***
	(1.4179)	(8.0817)	(28.3797)	(1.4722)	(36.4321)
$\boldsymbol{\phi_{rl}}$	0.2445***	0.3102***	-1.0113***	0.2102***	-0.5014***
	(3.5365)	(2.5884)	(-8.1006)	(2.8218)	(-3.9627)
Rel. 2–5 yrs		-0.0052			-0.6233***
		(-0.0395)			(-15.2042)
Rel. 6–10 yrs		-0.5282***			-0.9199***
		(-3.1001)			(-16.2391)
Rel. 11–15 yrs		-0.3859*			-0.2198
		(-1.6960)			(-1.3725)
Rel.$\geq$ 16 yrs		0.3455			0.9699***
		(1.5460)			(4.4651)
Rel. with DEO			2.3144***		2.4923***
			(17.7444)		(18.0595)
Rel. with CU			-17.8455***		-21.9760***
			(-122.9423)		(-104.1102)
Rel. with SCB			0.0328		0.1473
			(0.1522)		(0.7162)
Rel. with Others			1.1211***		0.9832***
			(5.8788)		(4.2201)
Rel. Market Share				3.2764	-26.1903***
				(1.1947)	(-16.8716)
Pseudo R^2	0.0000	0.0128	0.0107	0.0001	0.0270
Observations	889,889	889,889	889,889	889,889	889,889

Appendix

A1 HMDA-Verisk Data vs HMDA Data

This section compares the yearly average loan amount, loan term, and loan interest rate between HMDA-Verisk Data and HMDA Data.

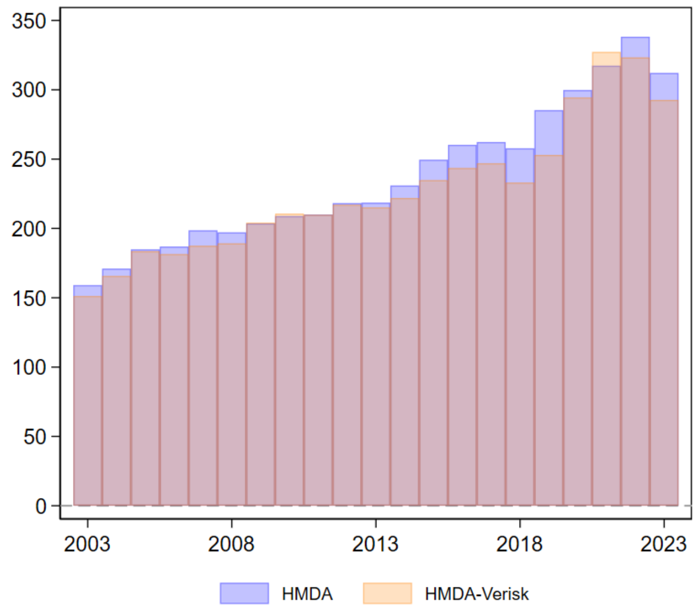


Figure A1: Loan Amount(k)

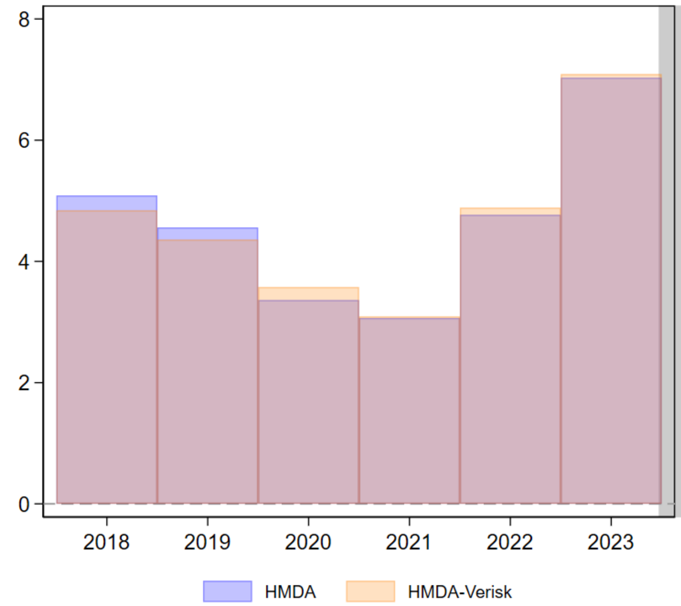


Figure A2: Loan Interest Rate(%)

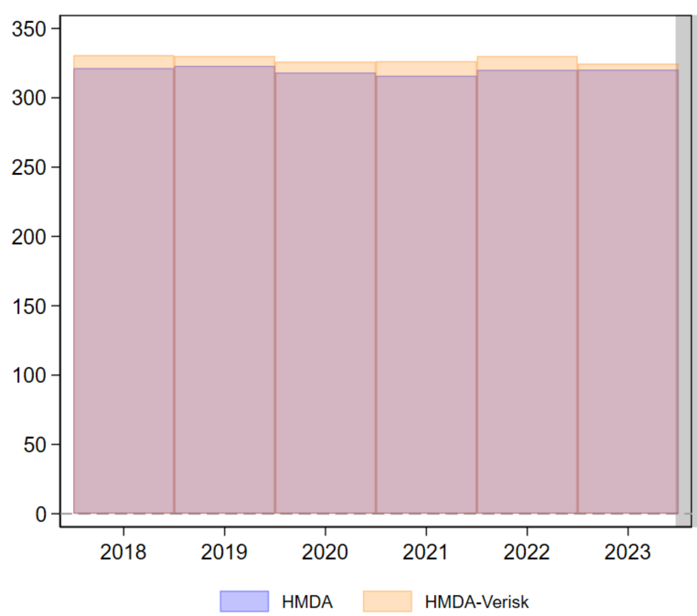


Figure A3: Loan Term(month)

A2 Example of an Angry Customer

Following the merger, Truist transitioned around seven million legacy SunTrust customers to a new digital system and rebranded 2,000 branches in 2022. The integration was widely criticized for poor technical migration and inadequate customer communication, leading to widespread customer dissatisfaction. 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. Two months after the integration, the Consumer Financial Protection Bureau reported that the number of complaints filed against Truist had increased by more than 81 percent.

Following graphs presents a complaint from an angry and frustrated customer.

> Last month, [illegible], 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. Did I mention your website sucks?”

A3 Mortgage Refinancing Probability: Acquirer-Matched Sample

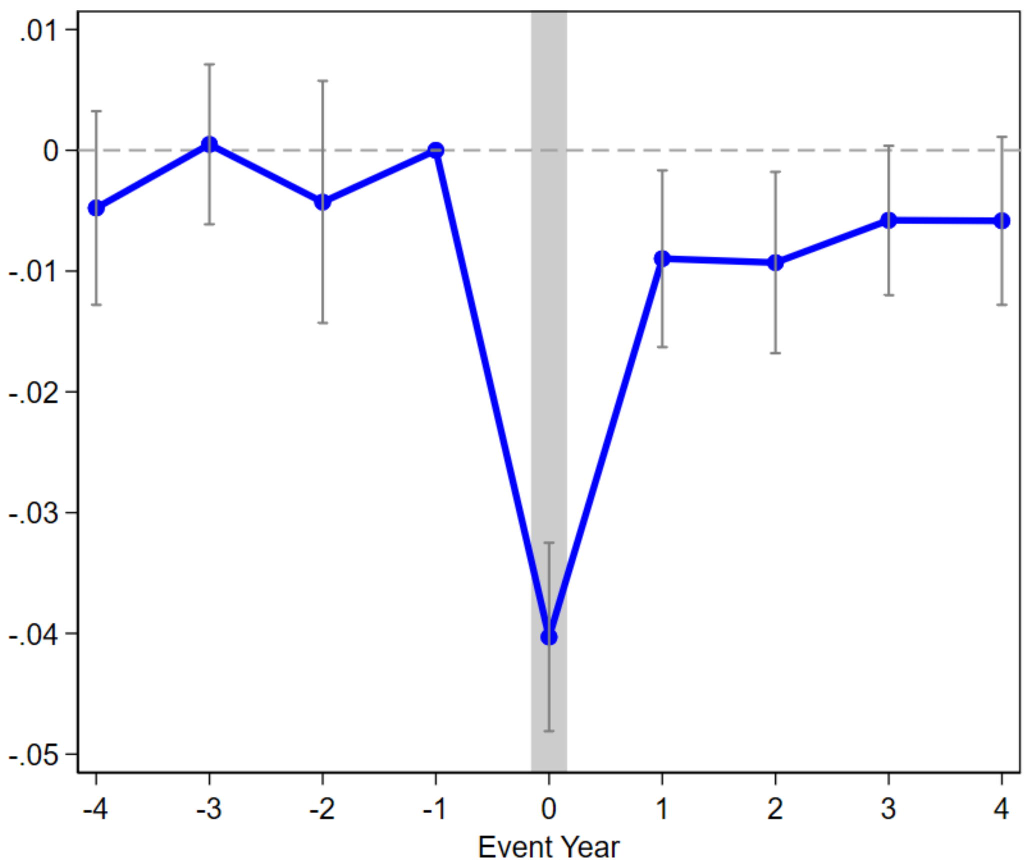


Figure A4: Mortgage Refinancing Probability: Acquiror-Match Sample

Note: This Figure plots the coefficients of $IfRefi_{i,t} = \alpha + \sum_{\delta=[-4,4],\delta\neq-1} \beta_\delta \mathbf{1}(Treated)_i \times \mathbf{1}(t=\delta)_t + \tau_i + \gamma_\delta$ using a matched sample. The dependent variable $IfRefi_{i,t}$ takes 1 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 fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the incumbent mortgage. Each treated household is matched to control households located in the same county, holding comparable incumbent loans prior to the bank M&A shock, whose incumbent relationship lender is the acquiring bank.

Table A1: Mortgage Refinancing Probability: Acquiror-Matched Sample

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a Acquiror-Matched sample. The dependent variable in column (1) takes 1 if household i refinances in year t, the dependent variable in column (2) takes 1 if household i refinances with the relationship lender in year t, the dependent variable in column (3) takes 1 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the incumbent mortgage. Each treated household is matched to control households located in the same county, holding comparable incumbent loans prior to the bank M&A shock, whose incumbent relationship lender is the acquiring bank. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	IfRefi	IfRefi with Relationship Lender	IfRefi with New Lender
Treated × Post	-0.014***	-0.005***	-0.008***
	(-8.192)	(-4.711)	(-6.901)
Household FE	YES	YES	YES
Event Year FE	YES	YES	YES
Observations	83494	83494	83494
R^2	0.131	0.140	0.134

A4 Mortgage Refinancing Probability: by Demographics

Table A2: Mortgage Refinancing Probability: by Demographics

This table reports the coefficients of $IfRefi_{i,t} = \alpha + \beta \mathbf{1}(Treated)_i \times \mathbf{1}(t = \delta)_t + \tau_i + \gamma_\delta$ using a matched sample. Column (1) reports results adding a crossing term of If Large Family Size, column (2) reports results adding a crossing term of If High Age, column (3) reports results adding a crossing term of If Anyone Went to College, and (4) reports results adding a crossing term of If Anyone Works in Finance Industry. The dependent variable takes 1 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 $\mathbf{1}(Post)_t$. The regression includes household fixed effects and event-year fixed effects. Treated households are those whose relationship bank was acquired, with the M&A year designated as event year zero. The relationship bank is defined as the originator of the existing mortgage. Each treated household is matched to control households located in the same county, holding comparable existing loans prior to the bank M&A shock, but never experienced a bank M&A shock. t-values are reported in parentheses. Standard errors are clustered at the household level.* <0.1 ** <0.05 *** <0.01.

	IfRefi	IfRefi	IfRefi	IfRefi
Treated × Post × 1(LargeFamily)	0.0005			
	(0.1906)			
Treated × Post × 1(HighAge)		-0.0044*		
		(-1.7978)		
Treated × Post × 1(College)			0.0048*	
			(1.6614)	
Treated × Post × 1(Finance)				0.0165***
				(2.8323)
Treated × Post	-0.0111***	-0.0089***	-0.0153***	-0.0100***
	(-6.7235)	(-5.1531)	(-6.0761)	(-7.1642)
Household × Subgroup FE	YES	YES	YES	YES
Event Year × Subgroup FE	YES	YES	YES	YES
Observations	318506	309399	291046	230594
R^2	0.133	0.132	0.132	0.130

A5 Mortgage Refinancing Probability from NMDB

In the construction of sample used for structural estimation, I re-balance the sample such that the sample average of refinancing probability matches the refinancing rate estimated using the NMDB. The NMDB, published by Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB), reports the national number of outstanding single-family mortgage loans since 2013, as well as the national number of refinance loan originations. The refinancing rate each year is calculated as national number of refinance loan originations divided by the national number of outstanding loans at the end of last year. Following table report the refinancing rate estimated using the NMDB from 2014 to 2023.

Table A3: Mortgage Refinancing Probability from NMDB

Year	Refinancing Probability
2014	0.0481
2015	0.0678
2016	0.0807
2017	0.0567
2018	0.0425
2019	0.0755
2020	0.1731
2021	0.1696
2022	0.0478
2023	0.0175