Mortgage Put-Back Risk and Lender Market Power in Refinancing*

2025-03-03

Abstract

This paper examines the welfare implications of put-back risk in the U.S. refinancing market for GSE-securitized loans. Put-back provisions allow GSEs to require lenders to repurchase defective loans, shifting credit risk back to lenders. Put-back risk surged post-2008, disproportionately affecting high-LTV refinancing with non-incumbent lenders. We develop and estimate a dynamic refinancing model where incumbent's advantage stems from search frictions and asymmetric put-back risk. Our identification exploits a 2013 policy reform that reduced and equalized put-back risk. We show that reducing put-back risk significantly benefits borrowers without harming GSEs or MBS investors. Correcting the asymmetry alone achieves similar welfare effects.

Keywords: Refinancing, Market power, Search friction, Mortgage repurchase, Financial crisis
JEL Classification Codes: G21, G51, L51

*This paper subsumes a prior working paper "Unintended Consequences of the Home Affordable Refinance Program".

1 Introduction

Government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac acquire loans from mortgage lenders and securitize them into agency mortgage-backed securities (MBS). Although GSEs insure lenders against potential credit loss through government guarantees, they retain the right to mandate a repurchase when the loan is found to violate their underwriting guidelines, thereby transferring the credit risk back to the lender. This forced repurchase is known as a mortgage put-back. The put-back provision is established to mitigate the agency friction and incentivize thorough due diligence among lenders. However, depending on the enforcement policy, it can also exacerbate competitive frictions, raising lending costs and deterring borrowing.

This paper examines the welfare implications of the put-back risk in the post-2008 financial crisis period, focusing on its competitive effects in the U.S. refinancing market. Historically, mortgage put-back risk in the mortgage market was low, but surged in the aftermath of the 2008 financial crisis. As mortgage defaults increased, GSEs aggressively enforced put-back provisions, requiring lenders to repurchase delinquent loans deemed defective. At the same time, policymakers sought to encourage refinancing for high loan-to-value (LTV) borrowers as a way to stabilize housing markets and stimulate the economy. These borrowers had negative or minimal home equity after the housing crisis and were unable to refinance due to traditional LTV limits, despite the falling interest rate and potential interest savings. The Home Affordable Refinance Program (HARP), introduced in 2009, expanded refinancing opportunities by lifting LTV restrictions and relaxing underwriting standards.[1]

However, high-LTV refinancing was plagued by lender's concern over its heightened put-back risk, and the asymmetric risk exposure depending on whether it was a same-lender refinance. Incumbent lenders, who had originated the legacy mortgages, faced lower put-back exposure than other competing lenders due to a preferential treatment inadvertently created

[1]To control credit risk, HARP required borrowers to have a good payment history. Specifically, they should be current on their mortgage payments, with no payments more than 30 days late in the last six months and no more than one late payment in the last 12 months.

by the implementation of put-back policies (Goodman, 2011; Agarwal et al., 2023). This in turn created an asymmetry in the expected cost of refinancing between the incumbent lenders and their would-be competitors under HARP, enhancing the market power of the former and lowering their incentive to offer a competitive rate.[2] In the face of these distortions, in 2013 policymakers introduced significant reforms to clarify lenders' repurchase exposure, significantly reducing the put-back risk and leveling the playing field for all lenders.[3] The new policy would particularly benefit high-LTV refinancing under HARP, however, by this time, the majority of HARP refinancing had already taken place.[4]

To assess the welfare implications of put-back risk, in this paper we develop a dynamic refinancing model where borrowers negotiate interest rates with differentiated lenders. The model incorporates put-back risk into lenders' pricing decisions and allows incumbency advantage due to its asymmetry and the search friction. We structurally estimate the model using loan-level data and exploit the 2013 put-back policy change in our identification. We find that put-back risk has significant welfare consequences, especially through the market power channel. In addition, a higher put-back risk does not always benefit GSEs and investors, as their profits hinge on the refinancing volume and timing.

The dynamic refinancing model starts with mortgage origination, after which borrowers face a default shock at the start of each period.[5] If no default occurs, the borrower observes the updated state variables, including an idiosyncratic housing shock and market conditions such as the MBS coupon rate and the house price index. These variables determine their

[2]According to Goodman (2011), "The most fundamental problem—if the same servicer is the only one who can refinance the borrower, there is no incentive for that servicer to offer a competitive rate".

[3]Under the revised framework, GSEs conduct thorough reviews of mortgages shortly after acquisition, enabling the early detection of underwriting defects. This proactive approach aims to facilitate prompt corrective actions and prevent issues that could lead to loan repurchases. Additionally, the new policy explicitly relieves lenders of repurchase obligations under certain circumstances and ensures equal treatment for refinanced mortgages, regardless of whether the lender is the incumbent.

[4]The uptake of HARP refinancing had been declining since its peak in 2012. One reason is that HARP was originally set to expire at the end of 2013. Many HARP borrowers refinanced in 2012 after significant enhancements to HARP was enacted in that year. Second, borrowers' LTV ratios declined over time as the housing market recovered, and those who hasd already taken HARP were not allowed to take the program again. So the pool of eligible borrowers shrank over time.

[5]Default probability is given by a function of borrower and loan characteristics.

current LTV ratios and cost of funds for mortgage lenders. The borrower then makes a discrete choice of whether to refinance and enters the two-stage price negotiation process.[6] The incumbent lender makes an initial offer in the first stage, and the borrower can either accept it or reject it to search for competing quotes.

The borrower weighs the expected benefit of obtaining a better rate against the cost of searching, which is motivated by our empirical evidence. Prior to 2013, 84% HARP borrowers refinanced with their incumbent lenders and paid, on average, 12 basis points (bps) more than those who switched to competing lenders, conditional on observed characteristics. These patterns are consistent with the presence of search frictions in the refinancing market (Allen et al., 2019; Allen and Li, 2025). In the model, the incumbent lender's first-mover advantage creates a quasi-monopoly position, allowing them to charge higher markups for borrowers with high search costs or poor outside options due to high expected put-back cost faced by competing lenders.

Lenders face an expected put-back cost proportional to the put-back probability, which is a function of borrower and loan characteristics, time period, and lender type. In the time periods before 2013, incumbent lenders face a lower put-back probability than competing lenders, but in the following time periods, put-back probability is reduced and equalized across all lenders, as suggested by our empirical findings. Before 2013, a HARP refinance with the incumbent lender was half as likely to be put back compared to the one with a competing lender. This gap in put-back probabilities disappeared following the 2013 changes. In addition, all lenders had a significant reduction in put-back probabilities after 2013. The policy changes not only directly lowered lenders' expected put-back costs but also reduced incumbent lenders' markups by weakening their market power.

Lenders collect monthly payments and pass on guarantee fees (g-fees) to GSEs and coupon payments to MBS investors. The g-fees are functions of LTV and borrower characteristics and make up GSEs revenue. GSEs also bear credit risk exposure, with expected credit losses

[6]If the current LTV satisfies the eligibility criteria of HARP, the borrower considers HARP refinancing with an exogenous probability; otherwise the borrower only considers regular refinancing.

decreasing with put-back probability. A lower put-back probability reduces the likelihood that lenders repurchase defective loans, increasing GSEs' direct exposure to defaults. However, reduced put-back risk can also boost g-fee revenue due to increased refinancing activities and an earlier refinancing timing. Refinancing a mortgage extends the total amortization period, generating g-fee payments for a longer duration. Thus, g-fee revenue increases when more borrowers refinance. A more nuanced effect comes from refinancing timing: since g-fee increases with LTV at refinancing, borrowers who refinance earlier generally have a higher LTV and therefore generate higher g-fee revenue.

MBS investors receive coupon payments, which are reset to the current rate only if underlying mortgages are refinanced. They are generally disadvantaged by higher refinancing activity, as new loans typically carry lower coupon rates. However, in the post-crisis period with declining rates, earlier refinancing can lock in relatively higher coupon rates, mitigating investor losses. Therefore, the net impact of put-back policy change on the profits of GSEs and investors is an outcome of the interaction between changes in both the extensive margin (refinancing activity) and the intensive margin (refinancing timing), whose contributions can be assessed separately in the model.

For estimation we use a sample of homeowners with 30-year fixed-rate mortgages owned by Freddie Mac that were originated between 2003Q1 and 2006Q4 for the purpose of purchasing a property. For each mortgage, we observe one of four outcomes in every period up to mid-2018: refinanced with HARP, prepaid without HARP, default, or no action. For those who refinanced with HARP, we also observe the interest rate and lender identity. The model is estimated using maximum likelihood.

Estimation results shows that put-back risk constitutes an economically significant component in lenders' expected cost. In the pre-2013 period, the average expected put-back cost for a competing lender is \$7.90 per \$100 of the mortgage, while for an incumbent lender it is \$3. This leads to a cost advantage of \$4.90 in terms of put-back risk, while the cost differential from all other sources is less than a dollar.

Our counterfactual analysis shows that changes in put-back policies have considerable welfare consequences. If the put-back policy had been revised immediately after the crisis, borrowers would have experienced significant welfare gains. On average, the welfare of all sampled borrowers would have increased by approximately $4,012 compared to the baseline. Notably, nearly half of these gains can be achieved by correcting the asymmetric risk exposure alone—eliminating the market power channel of put-back risk. This welfare impact is comparable to, and sometimes exceeds, that of the search friction, a well-established source of inefficiency in the mortgage market.

The welfare increase for borrowers does not come at the expense of GSEs and investors. In our counterfactual scenario, both groups benefit marginally. For GSEs, two factors drive these gains. First, the policy change stimulates refinancing on the extensive margin. Although the effect is small (about 0.3 percentage points), GSEs earn substantially more from refinancing borrowers than from non-refinancing ones, so even a modest increase in refinancing activity yields significant additional revenue. Second, on the intensive margin, borrowers tend to refinance earlier with higher LTVs, which also boosts g-fee revenue. These revenue gains largely offset any small increase in default losses from changes in put-back policies.

MBS investors also benefit from the change in refinancing timing. In a declining rate environment, earlier refinancing locks in relatively higher coupon payments, which offsets the negative impact of increased refinancing volumes. As a result, investor profits show a slight improvement compared to the baseline.

Our results underscore the economic implications of put-back risk in mortgage refinancing, especially in the post-crisis period, and continue to be relevant in the context of the recent policy developments. After the COVID-19 pandemic, concerns over put-back risk resurfaced, as repurchases demands rose and the cost of repurchases increased due to a rising-interest-rate environment.[7] Moreover, lenders were uncertain about the put-back policies for

[7] When lenders are forced to repurchase loans, they often attempt to resell them in the secondary market as part of a "scratch and dent" package with significant discounts. As time elapses since the loan origination, the prices of those loans fall with rising interest rates, magnifying the put-back loss to the originator.

loans, whose borrowers have elected a COVID-19 pandemic forbearance. In response, FHFA adjusted the policy for loans subject to the forbearance programs in October 2023. Freddie Mac subsequently announced a pilot offering a more transparent fee-based alternative to repurchases for performing loans. However, it began with a "limited rollout to a targeted group of lenders". Lessons from our study suggest that in mortgage markets already characterized by competitive frictions, specialized treatments for certain groups of lenders may lead to significant welfare implications by reinforcing their market power. Therefore, such policies need careful discussions of their competitive impacts, as they might have first-order effects by exacerbating competitive frictions in these markets.

Related Literature Our paper contributes to the literature on refinancing behaviors. Agarwal et al. (2013) (thereafter, ADL) derive a closed-form solution of the optimal refinancing threshold of the rate gap, i.e., the difference between the original mortgage rate and the current rate.[8] Many empirical studies have since found systematic deviations between real-life refinancing behaviors and the ADL rule. For instance, Keys et al. (2016) use a sample of US mortgages in December 2010 and find that approximately 20% of households did not refinance despite meeting the ADL threshold. Agarwal et al. (2016) find approximately 57% of US borrowers refinance suboptimally—either refinancing at a rate gap that is too small or waiting too long to refinance. Both behavioral and financial frictions have been explored as potential explanations for these deviations. Andersen et al. (2020) estimate an empirical model using the ADL threshold and find fixed psychological costs and inattentive behavior contribute to the slow refinancing observed among Denmark households. Byrne et al. (2023) further confirm the role of consumer inattention using a field experiment on Irish households. Berger et al. (2024) extend the ADL model to account for inattentive borrowers, which partially rationalizes previously documented deviations. DeFusco and Mondragon (2020) find that requiring borrowers to document employment and pay upfront costs introduces eco-

[8]The ADL model makes several important simplifying assumptions, including infinite maturity, an exogenous Poisson repayment event, and Brownian motions for the real mortgage interest rate and inflation.

nomically meaningful frictions to mortgage refinancing. More related, Ambokar and Samaee (2019) explore the role of search costs in explaining refinancing inaction. Their model builds on Arcidiacono and Miller (2011) and incorporates unobserved search costs.

This paper contributes to this literature by highlighting how competition frictions affect refinancing decisions and borrower welfare. We also show how policies may exacerbate such frictions and lead to significant welfare consequences. We find that although search friction and fixed refinancing costs are important factors in borrowers' refinancing decisions, competitiveness of the refinancing market also plays a significant role. While addressing behavioral biases in borrowers can be costly and ineffective, policy interventions on the supply side may offer a more cost-effective way to boost refinancing activities by leveling the playing field and promoting competition.

Additionally, this paper connects to the literature on the agency conflicts in residential mortgage securitization.[9] These conflicts have long been recognized by market participants and various economic incentives and legal constructs are used to mitigate them (Frame, 2018). Most recent empirical studies focus on private mortgage securitization market where asymmetric information is more severe. Their findings suggest that investors do price in the elevated asymmetric information especially for low-documentation loans, and that agency cost-reducing mechanisms on the issuer side can partially alleviate these concerns (Demiroglu and James, 2012; Begley and Purnanandam, 2017; Adelino et al., 2017). This paper, by contrast, studies the agency MBS market with its more established mechanisms to reduce agency costs, and focuses on put-back provisions, which represent one of the most important such mechanisms. We examine the side-effects of put-back provisions when applied in an overly stringent or inconsistent manner. Our findings provide a more balanced perspective on the role of agency cost-reducing mechanisms in the primary mortgage market.[10]

This paper also fits into the literature that examines market power in household finance.

[9]See Frame (2018) for an extensive review of related empirical research on US home mortgages.

[10]The U.S. mortgage market is organized into two segments, primary and secondary. The primary market is where borrowers and lenders meet and negotiate lending terms to create a mortgage transaction, while the secondary market trades mortgage loans and MBS.

Previous studies (Woodward and Hall, 2012; Honka, 2014; Scharfstein and Sunderam, 2016; Allen et al., 2019; Agarwal et al., 2020; Allen and Li, 2025) have documented various sources of market power in consumer finance. We add to this literature by highlighting the effect of securitization-related policies on market power in the U.S. refinance market and quantify their economic impact.

Finally, our empirical findings are related to studies on HARP, most notably Agarwal et al. (2023), who examine the change in HARP interest rate following the 2013 policy change in put-back risk. Our study extends these findings by quantifying the broader welfare effects, not just for borrowers but also for GSEs and investors. While one might assume that reduced put-back risk could harm GSEs and investors by increasing their exposure to defaults, we show that higher refinancing activity and better timing can actually improve their overall financial outcomes.

2 Institutional Background

2.1 Mortgage Put-Back

In the U.S., GSEs acquire conforming mortgages from mortgage lenders, bundle them into agency MBS, and guarantee full payment of interest and principal to investors on behalf of lenders. GSEs charge lenders guarantee fees for providing the guarantee.[11] Lenders that securitize loans through GSEs typically retain mortgage servicing rights, which constitute their main source of cash flow.[12]

When selling mortgage loans to the GSEs, lenders must assure that the loan selling and

[11] There are two types of guarantee fees: ongoing and upfront. Ongoing fees are collected each month over the life of a loan. Upfront fees are one-time payments made by lenders upon loan delivery to an Enterprise, which is often converted to an annual equivalent. Ongoing fees are based primarily on the product type, such as a 30-year fixed rate or a 15-year fixed rate loan. Upfront fees are used to price for specific risk attributes, such as the LTV ratio and credit score (Federal Housing Finance Agency, 2019). The choice between these fee structures depends on the agreement between the lender and the GSEs.

[12] The role of a servicer includes collecting payments, advancing them to the MBS trustee, and engaging in various loss-mitigating actions on delinquent loans. The terms "servicer" and "lender" are used interchangeably.

servicing processes comply with the guidelines outlined by the GSEs. These are formally known as representations and warranties ("reps and warrants") contracts.[13] Reps and warrants relate to factors such as mortgage underwriting, borrower eligibility, the mortgage product, the property, and the project in which the property is located. With this assurance, the GSEs do not need to conduct a thorough evaluation on each individual loan when purchasing from the lender, which streamlines the loan delivery process and facilitates the growth of the U.S. mortgage market. The GSEs can, however, conduct reviews on any loan after its delivery. If the GSEs determines that the loan violates any of the reps and warrants, the GSEs are entitled to require the lender that delivers the defective loan to buy it back. This forced repurchase is referred to as a loan put-back. A loan put-back is highly costly for the lender because the GSEs typically conduct reviews when a loan shows signs of delinquency. By buying back the loan, the lender could bear the associated credit loss.

Figure 1: Put-Back Ratio on Delinquent Loans by Year

Figure 1 plots the fraction of loans that result in a repurchase among all delinquent loan in a given year. We define delinquency as having overdue payments for over 60 days. This sample include Freddie Mac single-family mortgages originated after 2000.

[13]See https://www.fhfa.gov/policy/representation-and-warranty-framework.

Mortgage put-backs, however, were uncommon prior to the Global Financial Crisis (GFC) in 2008. In Figure 1, we plot mortgage put-back ratio by year, calculated as the number of put-backs in each year divided by the total number of delinquent loans, since those loans were most likely to be audited by the GSEs. Before 2008, the ratio of put-back among delinquent loans was around 2%. During the GFC, with large waves of mortgage defaults, the GSEs became more aggressive in terms of auditing the delinquent loans for any defects and breaches of reps and warrants contracts. As a result, put-backs peaked following the crisis, when the rate of put-back tripled compared to pre-crisis levels.

2.2 HARP Program and Put-Back Issues

With the collapse of the U.S. housing market during the GFC, many borrowers had near zero or negative equity in their home as house prices fell (i.e. they became "underwater"). This prevented them from refinancing their mortgages because lenders typically require an LTV ratio of no more than 80% for refinancing.[14] As a consequence, these borrowers were unable to lower their mortgage payments through refinancing in the post-crisis low-rate environment. In response, the federal government together with the GSEs developed HARP in 2009 to expand the set of borrowers who could refinance their loans. The goal was to help underwater borrowers regain access to the refinance market, which could lower their mortgage payments and thus reduce mortgage default rates.[15] Crucially, the program generally allowed each borrower to use HARP only once.

In 2012, HARP went through major modifications which resulted in HARP 2.0 (Federal Housing Finance Agency, 2013). This enhancement of HARP targeted three main areas. First, it streamlined the refinancing process and reduced refinancing costs by lowering cer-

[14]The maximum LTV that lenders are willing to accept is 95% if the borrower is willing to pay an upfront mortgage insurance premium.

[15]Specifically, the program allowed borrowers with LTV ratios higher than 80% to refinance their mortgages by extending federal credit guarantees on those loans. Other qualification requirements included no delinquency record in the previous 12 months and that the original mortgage was owned by a GSE. See https://www.fdic.gov/resources/bankers/affordable-mortgage-lending-center/guide/part-1-docs/freddie-home-affordable-refinance-program.pdf.

tain costs and fees and relaxing the home appraisal requirement.[16] Second, it removed the 125% LTV ceiling of HARP refinancing, which expanded the eligibility criteria to include deeply underwater borrowers. Last but not least, a nationwide public relations campaign was launched to educate borrowers and increase their awareness about HARP. Previously, public awareness of the program was low, and borrowers were also uncertain about the program rules. The program was initially set to expire at the end of 2012, with a series of subsequent announcements extending that deadline. The program officially ended at the end of 2018.

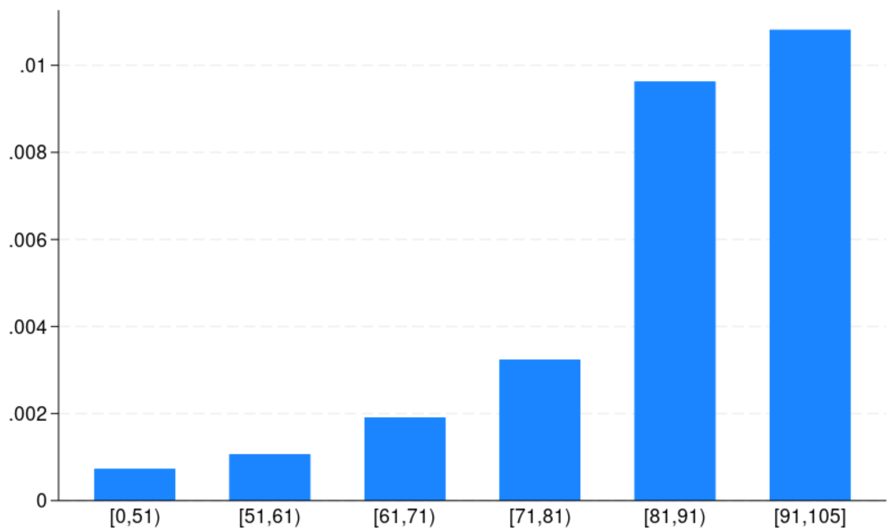


Figure 2: Put-Back Ratio by LTV

Figure 2 plots the fraction of loans that result in repurchases among all loans in Freddie Mac single-family mortgages originated between 2003 to 2006. The fraction is shown for each group of LTV at origination.

From lenders' perspective, put-back risk was one of the most prominent concerns for HARP in its early years. This is because high-LTV loans were associated with a higher delinquency rate, and thereby more likely to be audited and reviewed by the GSEs and result in repurchases.[17] As shown in Figure 2, only 0.2% of borrowers with LTV $\leq$ 80 resulted in a mortgage put-back, whereas 1% of high-LTV borrowers (i.e., LTV over 80%) have their mortgages put back from GSEs. In other words, a lender's exposure to put-back

[16] HARP 2.0 permitted lenders to use automated valuation models in lieu of traditional property appraisals.

[17] According to Goodman (2011), if a new loan goes delinquent in the first 6 months, Freddie and Fannie usually conduct a review of the loan file which could lead to repurchase.

risk when originating a high-LTV mortgage is five times as high as a regular mortgage. Therefore, lenders were generally hesitant to accept high-LTV mortgages.

However, same-lender refinancing were less affected by the heightened put-back risk due to two reasons. First, although both same-lender and new-lender refinances required lenders to provide new representations and warranties on the refinanced loans, new lenders are more wary of potential repurchase demands, as they had to vouch for loans they did not originate and take on additional risk (Goodman, 2011). Second, incumbent lenders retained all the relevant documents, records, and payment history from the original mortgages, which could serve as additional proof of due diligence when audited. Thus, the risk of mortgage put-back fell unevenly on lenders, depending on whether they had a previous relationship with the borrower or not (Agarwal et al., 2023).

2.3 The 2013 Policy Change on Mortgage Put-Back

In response to these issues, the GSEs and FHFA launched a new framework for the enforcement of the reps and warrants, effective January 1, 2013 (Federal Housing Finance Agency, 2014). The goal of the new framework was to reduce uncertainty for lenders by clarifying lenders' exposure and liability to loan put-back. First, the new framework established a unifying criterion for a loan to be relieved from the reps and warrants liabilities and thus a future put-back. For HARP loans, lenders were spared from loan put-back if the HARP borrower made on-time payments during the first 12 months after the acquisition of the loan by the GSEs. Second, the new framework directed the GSEs to evaluate loan files and identify potential defects earlier in the loan process, rather than when a loan defaults. Early quality control reviews like this avoid the worst outcome, namely to put-back a defaulted loan and let the lender bear all the credit loss. Third, the review process is conducted on a more consistent and systematic basis, rather than using discretion and relying on isolated instances of misstatements and misrepresentations (Goodman et al., 2013, 2015).

Overall, the new framework relived lenders from certain reps and warrants liabilities and clarified the level of due diligence and underwriting efforts needed to prevent mortgage put-back. Under the new framework, documents or history from the previous relationship no longer play a significant role, thereby minimizing the incumbency advantage. With transparent enforcement rules, lenders other than the incumbent lender could now manage the put-back risk to a similar degree as the incumbent lender. In the next section we perform two descriptive analyses using the HARP sample to illustrate that the data pattern is consistent with the discussion in this section.

3 Data

Our data come from three sources. The first is the single-family loan-level dataset from Freddie Mac. The second is HARP, which are made public by Freddie to promote the transparency of the program. The third is the House Price Index from the FHFA, which measures the price movement of single-family houses. We then use the data to document the key features of the program.

3.1 Data Sources

Single-Family Loan-Level Dataset Freddie Mac started publishing single-family loan-level data to support risk sharing and transparency. The dataset starts in 2000 and are updated quarterly. It comprises two parts: acquisition and performance. The acquisition file provides the characteristics of loans acquired by Freddie at the loan origination level. The loan characteristics that we observe include credit score (FICO), LTV ratio, debt-to-income (DTI) ratio, loan amount, loan purpose (e.g., home purchase, cash-out refinance, or no cash-out refinance), quarter of origination, property ZIP code (three-digit), and the name of the lending institution. The performance file is a panel that provides monthly credit performance, which includes the monthly loan balance and delinquency status. The loan exits the performance file if it is terminated by the borrower via a prepay/refinance or foreclosure.

HARP Data The HARP data, which is a subset of the U.S. single-family loan-level dataset, uniquely allows us to link every HARP refinance to its previous mortgage information. This allows us to identify the households that were refinanced under the program, as well as constructing the key variables of the analysis, such as whether they refinanced with their incumbent lender and the interest rate reduction they received from HARP.

House Price Index We also use the FHFA House Price Index (FHFA HPI©). FHFA uses data on mortgage transactions from Fannie Mac and Fannie Mae to calculate the index using a modified version of the weighted-repeated sales methodology. This quarterly index measures changes in single-family home values at the national, census division, state, metro area, county, ZIP code, and census tract levels. We match borrowers in our main sample with the HPI at the three-digit ZIP code level, which is the finest geographic location disclosed by the single-family loan-level data. The HPI aids in the estimation of borrowers' home values after loan origination. The estimation procedure is discussed in detail in Section 5.1.2.

National Survey of Mortgage Originations We use the National Survey of Mortgage Originations (NSMO) as a complementary data source for search behavior. The NSMO survey represents a random sample of about 6,000 mortgages drawn quarterly from loans newly reported to one of the three national credit bureaus. It is a nationally representative sample of newly originated, closed-end, first-lien residential mortgages in the U.S. We use this external dataset to construct an auxiliary moment on search behaviors in our estimation.

3.2 Sample and Summary Statistics

3.2.1 Sample Construction and Variable Definition

Our sample consists of homeowners with a 30-year fixed-rate mortgage owned by Freddie Mac that originated between 2003Q1 and 2006Q4 with the purpose of purchasing a property.

We refer to the origination year as the cohort of a borrower. These "purchase mortgages" are referred to as the original mortgage. We obtain the loan and borrower characteristics on the original mortgages from the origination data file in the single-family loan-level dataset. This is then merged with the HARP origination data file, which contains the loan identification number of the corresponding legacy mortgage. This allows use to identify loans in the main dataset that are refinanced through HARP following their origination. Furthermore, the merged data contains the information on their subsequent HARP refinances, such as the interest rate, LTV ratio, and lender information. We consider a borrower to switch lenders if the lender on the HARP refinance is not the same as the lender on the original mortgage.[18] Since the single-family loan-level dataset does not provide specific lender names when a lender's market share is too small, we discard observations when both the previous lender and new lender's names are missing. We also do not include HARP mortgages that are not of standard term length.[19] These account for 21,542 observations, or 1% of the whole sample.

For each original mortgage, we construct the loan outcome variable from the monthly performance data file, which contains information on the repayment status of each loan up until June 2018, the end of the sample period. We classify each loan into four outcomes: default, HARP refinanced, other prepaid, and no action. Default includes two scenarios. First, the loan's balance is reduced to zero for reasons other than voluntary payoff. Second, the zero balance is due to voluntary payoff, but the loan is at least 90 days in delinquency in the last period before being paid off. We treat the second scenario as a voluntary default, likely caused by the owners selling their home voluntarily to avoid foreclosure. Other voluntary

[18] Technically speaking, we define a switching behavior when the servicer of the original mortgage is not the same as the seller of the new mortgage. This is because a mortgage's servicing right is often sold by the originator of the mortgage to other financial intermediaries after its origination. From the borrower's perspective, the servicer is the one with whom they directly interact and build familiarity at the time of refinancing. On the other hand, the seller of the new mortgage is more likely to be the one that interacts with the borrower during the refinancing process. We also used other ways to define switching and found similar results.

[19] We keep the three most predominant term lengths for HARP loans, which are 180 months (18%), 240 months (14%) and 360 months (64%).

payoffs that don't appear in the HARP dataset are considered "other prepaid." A loan is considered "no action" if it is still active by the end of the sample period.

3.2.2 Summary Statistics

Table 1 reports the summary statistics for a number of variables of interest. Panel A is the main data. This sample contains people who purchased a house before the crisis during 2003–2006. These are all purchase loans with 30-year fixed interest rates. Their FICO score on average is 729, and the LTV is on average 78%, or 22% down payment. The mean of initial interest rate is 600 bps, with an average loan size of $172,000.

Since HARP refinancing is most affected by the policy change due to the high LTV, we then focus on the subsample of HARP borrowers who refinanced before and after 2013. Panel B reports their characteristics and refinancing outcomes. First of all, between 2009–2012, FICO scores for HARP takers actually increased from 729 to 750, presumably because HARP has a requirement that borrowers cannot have a missing mortgage payment in 12 consecutive months. However, LTV for those borrowers increased from 0.78 to 1.04, suggesting a loss of home equity for those households as a consequence of the 2008 housing crisis. The (refinance) interest rate that households obtained from the program was 452 bps between 2009–2012, compared to 412 bps between 2013–2018, a period when the market interest rate (i.e., the cost of credit) also decreased.

The switching rate (i.e., the fraction of borrowers who refinanced with a different lender among all borrowers who refinanced) among HARP borrowers before 2013 is only 16% , which implies a market share of 84% for incumbent lenders, compared to a regular refinance market where the incumbent market share is 28% to 33% across different years (Agarwal et al., 2023). The switching rate increases to 27% after the policy change in 2013. Figure 3 plots the switch rate over time. It is low during the first half of the program due to the asymmetric put-back probabilities between incumbent and competing lenders. It started to gradually increase after the policy change in 2013. Finally, the probability of put-back also

Table 1: Loan-Level Summary Statistics

Panel A: GSE Single-Family Data, 2003–2006

	Mean	S.D.
Loan Characteristics		
FICO Score	729	54
LTV	0.78	0.14
Interest Rate (bps)	600	46
Loan Size (1,000$)	172	84
Cohort Distribution		
2003	0.25	0.43
2004	0.24	0.43
2005	0.27	0.44
2006	0.24	0.43
Loan Outcome		
Default	0.060	0.24
Other Prepaid	0.78	0.42
HARP Refinanced	0.088	0.28
No Action	0.075	0.26
# of Observations	2,124,685	

Panel B: HARP Refinance, 2009–2018

	2009–2012		2013–2018	
	Mean	S.D.	Mean	S.D.
FICO Score	750	59	732	74
LTV	1.04	0.26	1.06	0.27
Interest Rate (bps)	452	63	412	55
Loan Size (1,000$)	197	77	163	69
Switching Rate	0.16	0.36	0.27	0.44
Put-back	0.002	0.046	0.001	0.023
# of Observations	130,329		56,204	

This table presents descriptive statistics for the data source used in this paper. Panel A shows the statistics for the parent data, which is the main GSE data that contains purchase loans from 2003–2006. Panel B presents the HARP takers among those in Panel A. This is separated by those who participated in HARP before the 2013 policy change.

decreased by twofold following the policy change.

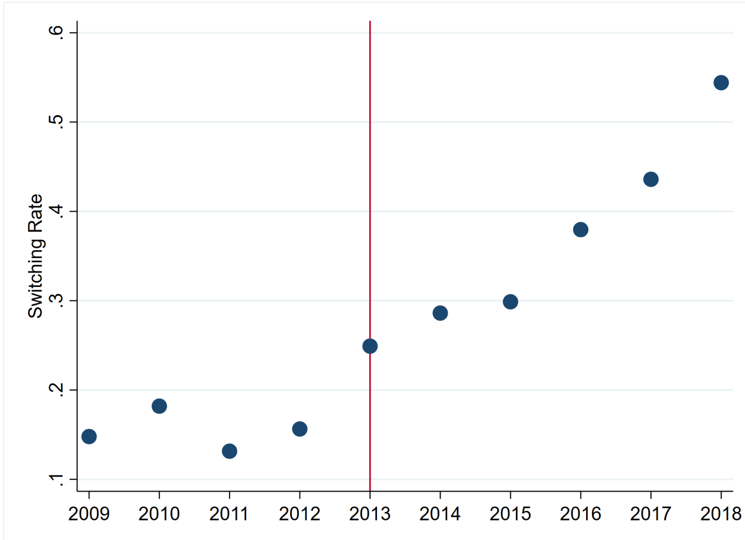


Figure 3: HARP Switch Rate Over Time

This figure shows the average switching rate among HARP borrowers in each year from 2009 to 2018. A borrower is considered to switch lenders if the lender on the new mortgage is not the same as the lender on the original mortgage.

Alt text: Chart depicting the fraction of HARP borrowers who switch to a new mortgage lender from 2009 to 2018, showing that the switching rate increased sharply after 2013.

3.3 Descriptive Analysis

In this section, we perform two descriptive analyses using the HARP sample to illustrate the effect of the 2013 policy change on put-back probability and prices.

3.3.1 The Effect of the 2013 Policy Change on Put-Back Probability

Since we can only observe switching behavior for HARP refinances, we use the put-back outcomes on HARP refinances to access the effect of the policy change. We estimate the put-back probability p^{PB} estimated via a logistic regression model:

$$p_{ij}^{PB} = \frac{\exp\left(X_{ij}'\hat{\delta}\right)}{1 + \exp\left(X_{ij}'\hat{\delta}\right)} \tag{1}$$

The dependent variable X_{ij} includes $Incumbent \times Pre$, $Post$, $Incumbent$, FICO, income, LTV and loan amount of the new mortgage, interest rate on the original mortgage, market-cohort fixed effects, and fixed effects for HARP origination year and HARP loan term. The dummy variable $Incumbent = 1$ indicates same-lender refinance, $Pre = 1$ indicates the period before 2013, and $Post = 1 - Pre$ indicates the post-change period.

Column (1) of Table 2 presents the estimates for δ. $Incumbent \times Pre$ has a negative effect, suggesting that during the first half of the program borrowers who refinanced through HARP with incumbent lenders were less likely to have their loans put-back than those who switched to competing lenders. The marginal effect is on average 0.23%, while the average put-back rate in the pre-2013 period is 0.45%, which makes same-lender refinances half as likely to be put-back than other refinances. The coefficient for $Incumbent$ is not statistically significant, suggesting that the asymmetry no longer holds in the second half of the program, which eliminates the difference between incumbent and competing lenders regarding put-back probabilities. Moreover, the policy change is also associated with a general reduction in put-back probabilities in the second half of the program, as is evident from the coefficient on $Post$. This is consistent with the policy background, which is intended to clarify lender's risk exposure, lower uncertainty, and create a level playing field for every lender. The marginal effect of the $Post$ is large, with an average of 0.53%. This suggests that the put-back risk is no longer a significant concern after the new policy.

3.3.2 The Effect of the 2013 Policy Change on Prices

We now examine the change in interest rate on HARP refinances after the new policy through a regression design shown in equation (2). We keep the same set of independent variables except for additional fixed effects of the incumbent lender's identity.

$$r_{ijtm} = \beta_0 + \beta_1 Incumbent_{ij} + \beta_2 \text{Post}_{it} + \beta_3 Incumbent_{ij} \times \text{Pre}_{it} + Z^{'}_{ijtm}\gamma + \epsilon_{ijtm}, \qquad (2)$$

Table 2: Descriptive Analysis

	(1) Put-back	(2) HARP Rate
Incumbent X Pre	-1.242^{**}	0.145^{***}
	(0.452)	(0.00748)
Post	-2.877^{**}	-0.411^{***}
	(1.054)	(0.0384)
Incumbent	0.158	-0.0248^{**}
	(0.433)	(0.00836)
LTV	0.00651^{*}	0.00185^{***}
	(0.00286)	(0.000108)
FICO	-0.00560^{***}	-0.000272^{***}
	(0.000943)	(0.0000547)
log(Income)	-0.712^{***}	0.00705^{**}
	(0.201)	(0.00228)
log(Balance)	0.647^{*}	-0.0729^{***}
	(0.255)	(0.00460)
Previous Rate	0.532^{**}	0.203^{***}
	(0.176)	(0.00536)
R-squared	0.116	0.702
HARP Orig Year FE	Yes	Yes
Seller FE	No	Yes
Cohort X Market FE	Yes	Yes
Observations	183,331	186,533

This table reports the results of the descriptive analysis using the sample of HARP loans (i.e., data from Panel B of Table 1). Column (1) reports the estimates for δ from a logit model in equation (1) where the dependent variable is put-back probability. The figures in parentheses are standard errors with 1, 2, and 3 asterisks indicating statistical significance at 10%, 5%, and 1%, respectively. R-squared is the pseudo R-squared from the logit model. Column (2) reports the coefficient estimates from a regression model in equation (2) where the dependent variable is the HARP refinance interest rate. The figures in parentheses are cohort-market clustered standard errors, with 1, 2, and 3 asterisks indicating statistical significance at 10%, 5%, and 1%, respectively.

Column (2) of Table 2 presents the results. Before the policy change, HARP borrowers with incumbent lenders on average pay 12 bps higher than those who switched to competing lenders.[20] This price difference exists despite incumbent lenders facing lower expected costs from put-back risk. One possible explanation is search friction—when the cost of searching for alternative lenders is high, borrowers may become effectively "captured" by their incumbent lenders. This grants incumbents a quasi monopolistic pricing power, allowing them to charge a higher markup than competing lenders. After the policy change, interest rates dropped significantly for both stayers (41 bps) and switchers (56 bps).[21] This is consistent with the cost-reduction effect of the 2013 policy. Note that the price differential between stayers and switchers is no longer positive after the policy change; it is negative but economically insignificant (2.5 bps), which could be a result of other cost differences between the incumbent and competing lenders. We do not find evidence supporting the information advantage of incumbent lenders, as there is no significant difference in default risk for stayers and switchers.

For quantification purposes, however, the regression results cannot be directly extrapolated. This is because the timing of refinancing is endogenous, and the early HARP takers can be unobservably different from the late HARP takers. Accounting for this calls for a structural model of borrowers' refinancing choices that endogenizes the timing of refinance given the market structure and program design. This model is described in the next section.

4 Model

Our model is finite horizon with discrete time periods. In the model, borrower i starts with an existing fixed-rate mortgage ($t = 0$). From the next year ($t = 1$), the borrower's dynamic refinancing problem begins. Let $m = 1, ..., N_M$ indicate the market in which the borrower is located. Mortgage lenders in the market are indexed by j. We reserve $j = 0$ for the

[20] 0.145 - 0.0248 = 0.1202.
[21] -0.411 - 0.145 = -0.556.

incumbent lender who serves the borrower's exiting mortgage, and $j = 1, ..., J_m$ for outside (competing) lenders.

4.1 Timing and information

At the beginning of each period t the borrower is faced with a probability of default $(1-p^C_{it})$. In the case of non-default, they checks their updated house value, h_{it}, and the current cost of funds in the market, c^m_t, to make a refinance decision. We assume that the change in their house value relative to the original house value at $t = 0$, denoted as $\Delta h_{it} = h_{it}/h_{i0}$, is a known function of the market-level change in house value, $\Delta h^m_t = h^m_t/h^m_0$, and an individual-specific temporary shock, q_{it}. The transition of the market-level variables $z^m_t = (h^m_t, c^m_t)$ is assumed as a Markov process. The idiosyncratic housing shock q_{it} is an i.i.d. draw from $N(0, \sigma_q)$, unobserved by the econometrician but known by agents in the model. The state variable is thus given by (z^m_t, q_{it}).

The updated house value determines the borrower's current LTV, and therefore their eligibility for HARP refinancing. Specifically, $LTV_{it} = h_{it}/L_{it} \times 100\%$, where L_{it} is the loan balance at the beginning of t. If $LTV_{it} < 80\%$, or it exceeds the ceiling imposed by HARP, the borrower is not qualified for HARP refinancing. Otherwise, they have both HARP and regular refinancing options.

These two refinancing options differ in the fixed costs borne by the borrower. We use ϕ^k_{it} to represent the time-varying refinancing costs, where $k = H$ (HARP) or $k = R$ (regular). It varies over time due to HARP's rollout. The first phase of HARP (HARP 1.0) lowers the refinancing cost compared to regular refinancing by explicitly reducing the monetary cost.[22] HARP 2.0 further streamlines the refinancing process with simplified rules and an appraisal waver, reducing both the monetary and *psychological* component of refinancing cost by cutting down the time needed to executing a refinancing and cognitive burden of

[22]The largest component is the private mortgage insurance for those with LTV over 80%, which is approximated by 1% of loan balance in the empirical specification.

navigating the complex rules.[23] We normalize ϕ to zero for HARP 2.0 refinancing. All time-invariant fixed utility effect of refinancing is summarized by a constant μ.

If the borrower decides to refinance and qualifies for HARP, we assume that they choose HARP refinancing with probability ξ_t. If the borrower is well informed about the program, ξ_t should equal 1 for because it dominates regular refinancing for qualified borrowers. A value of $\xi_t < 1$ indicates limited awareness of HARP. Similar to the HARP's fixed cost, the awareness also vary with different phases with its roll-out.

Given the type of refinancing, the borrower then negotiates a price with mortgage lenders through a two-stage process. In the first stage, the borrower contacts the incumbent lender. The incumbent lender makes an initial offer r_i^I. At this point, the borrower privately observes their search cost κ_i, which is a uniformly distributed random variable with mean $\bar{\kappa}$. Without loss of generality, we can write $\kappa = \bar{\kappa} \cdot \epsilon_i$, with $\epsilon_i \sim U[1-e, 1+e]$ and $e \in [0, 1]$.

Then, the borrower decides whether to take the initial offer or to reject it and search for a competitive offer by paying the search cost κ_i. If the initial offer is rejected, the borrower organizes an English auction among all lenders in the market and takes the lowest offer, thus ending the dynamic refinancing problem. If they choose not to refinance, they will still have the option of refinancing in the next period and the process continues.

Figure 4 summarizes the timing of events. Before solving the model, two remarks are in order. First, HARP imposes a one-time-only requirement, allowing each borrower only one chance to take advantage of the program. Therefore we assume that in the model a borrower has only one opportunity to refinance. Second, we assume that once a borrower decides to refinance at the beginning of a period, they commit to the refinance decision. In other words, they either take the incumbent's initial offer or the competing offer by the end of the period. This assumption greatly simplifies the game by ruling out non-refinance as an outside option in the price-setting game, thus making the model tractable.

[23]These psychological costs of refinancing reflects the value of the time spent on refinancing (e.g., gathering documents, filling out applications, and communicating with lenders), the cognitive and emotional burden caused by the uncertainty and complexity of refinancing, lost productivity and opportunity costs (Stanton, 1995; Andersen et al., 2020).

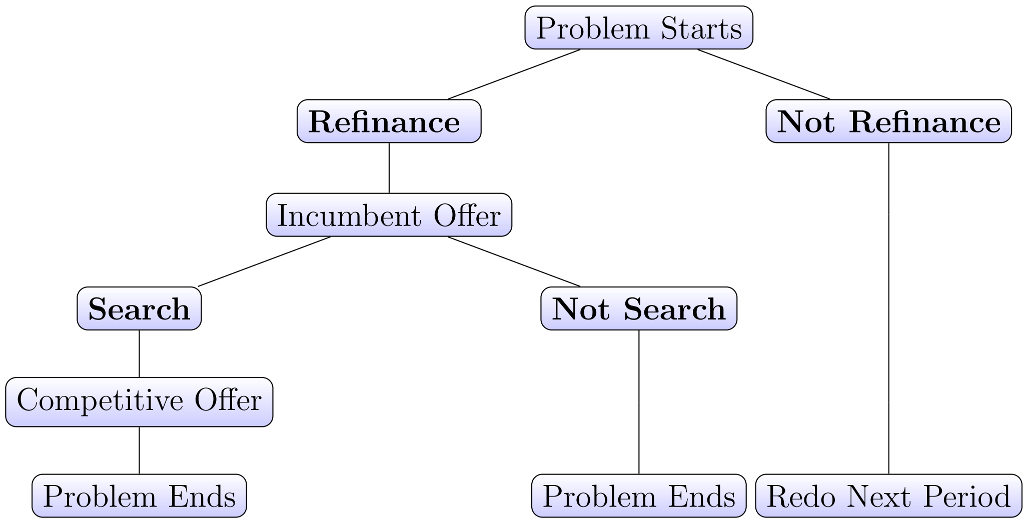


Figure 4: Timing of Borrower Decision

This figure shows the timing of borrowers' decisions. Borrowers first decide whether to refinance. If so, they decide whether to accept their incumbent lender's offer after receiving a free quote or pay a search cost to gain additional quotes. They must accept a competitive offer once they decide to search. If they decide not to refinance, they make the decision again in the next period.

Alt text: Graphical representation of the timing of borrowers' refinancing and searching decisions.

4.2 Utility and Profit Functions

We now specify borrower's expected utility and lenders' expected profits as functions of interest rate r. For the convenience of calculation, we convert all interest rates in this section to the *amortized* form.[24] Therefore the monthly payment to refinance the loan balance L_{it} at price r is given by rL_{it}.

Borrower's Refinancing Utility In this dynamic discrete choice problem, the decision to refinance is terminal, meaning that no further dynamic decisions will be required in subsequent periods after the refinancing choice has been made. This allows us to calculate a borrower's lifetime utility of refinancing at price r in period t in the following recursive form:[25]

[24] The relationship between amortized interest rate and annualized percentage rate $\tilde{r}$ (in %) is given by

$$r = \frac{\tilde{r}/1200}{1-(1+\tilde{r}/1200)^{-12\times T}}$$

[25] We abstract way from the borrower's saving choice and other non-mortgage borrowings.

$$U_{i\tau}(r) = u(y_i - m_i(r)) + \beta \left[p^C_{i\tau} U_{i,\tau+1}(r) + \left(1 - p^C_{i\tau}\right) \underline{U}_{i\tau} \right], \ \tau = t, ..., t+T. \tag{3}$$

Here, $u(\cdot)$ is the flow utility on consumption, which is income y_i net of annual mortgage payment $m_i(r) = 12rL_{it}$. β is the discount factor. p^C_{it} is the probability of non-default until the next period, $t+1$, conditional on non-default until period t. In other words, it is the probability that the borrower can continue to make the $t+1$th payment conditional on having made t payments. It is an exogenous function of borrower and loan characteristics as well as loan age.[26] $\underline{U}_{it}$ is the lifetime utility after default, given by $\sum_{\tau=t+1}^{\bar{T}} \beta^{\bar{T}-\tau} u(y_i) - h_{i0}$, where $\bar{T}$ is the last period of the borrower's life ($\bar{T} > T$). The terminal value of the recursive calculation is $U_{i,t+T+1} = \sum_{\tau=t+T+1}^{\bar{T}} \beta^{\bar{T}-\tau} u(y_i)$, which is the discounted sum of utility flows of a mortgage-free homeowner.

To facilitate the analytical derivation of price offers, we specify a linear utility function and therefore assume risk neutrality of borrowers: $u(y_i - m_i(r)) = y_i - m_i(r)$. It follows that $U_{it}(r)$ is also linear in r and can be represented by

$$U_{it}(r) = \bar{U}_{it} - \alpha_{it}\, r, \tag{4}$$

where the slope α_{it} varies with the time of refinancing, t, and the loan balance at the time of refinancing. We use this representation of $U_{it}(r)$ in the subsequent discussion.

Lender's Profit Function We assume in this model sell mortgages to the GSEs immediately after origination and retains the servicing right. For each dollar of the loan amount, r is the lender's incoming monthly cash flow, and the outgoing cash flow has two components: the guarantee fee paid to GSEs, denoted as g_{it}, and the coupon paid to investors, which is c_t. Similarly, we convert both g_{it} and c_t to amortized rates, so that $r - g_{it} - c_t$ is the net cash flow per dollar of the mortgage in each month. Following Fuster et al. (2013), we multiply

[26] We treat default as an event triggered by exogenous shocks rather than modeling it as a choice. In our empirical specification, we estimate p^C_t by using a survival function.

the net cash flow with a predetermined multiplier, M_{it}, to obtain the expected revenue per dollar throughout the span of the mortgage: $M_{it} \cdot (r - g_{it} - c_t)$. We assume that M and g are known functions of borrower i's characteristics and updated LTV_{it}.

To incorporate the put-back risk to the profit function, we define $P_{ijt} \equiv P_{cost} \cdot p_{ijt}^{PB}$ as the expected cost of a potential put-back, where P_{cost} is a cost parameter summarizing the total cost to the lender in the case of a mortgage put-back, and p_{ijt}^{PB} is the put-back probability, varying with borrower characteristics, lender and time to capture the put-back policy change.[27] Other time-invariant fixed cost at origination is denoted as F_j. In addition, there is an idiosyncratic shock to lender j's lending cost, ω_j, where the distribution of ω_j is given by a (minimum) Gumbel distribution with mean zero and scale parameter σ_ω. Therefore, the expected per-dollar profit of refinancing at price r is:

$$M_{it} \cdot (r - g_{it} - c_t) - P_{ijt} - F_j - \omega_j. \tag{5}$$

To facilitate analytical derivation, we assume all competing lenders share the same put-back probability given i and t, i.e., $p_{ijt}^{PB} = p_{ij't}^{PB}$ for $\forall j \neq j' \neq 0$. This allows us to define the incumbent's put-back risk advantage Δ_{it}^P as

$$\Delta_{it}^P = P_{ijt} - P_{i0t} = P_{cost} \cdot \left(p_{ijt}^{PB} - p_{i0t}^{PB}\right),\ j \neq 0, \tag{6}$$

where $\Delta_{it}^P > 0$ prior to the implementation of the put-back policy change, and $\Delta_{it}^P = 0$ following the policy change. We also normalize F_0 to zero and assume $F_j = F_{j'} = \Delta_F$ for $\forall j \neq j' \neq 0$. Therefore the total cost advantage of the incumbent is the sum of the put-back risk advantage and fixed-cost advantage, defined as $\Delta_{it} = \Delta_{it}^P + \Delta^F$. Finally, let $\pi_{ijt}(r) = M_{it} \cdot (r - g_{it} - c_t) - P_{i0j}$ represent the baseline profit, and we can simply the profit

[27] In our empirical specification, we use the estimated logit model of the put-back probability in Section 3.3.1 to proximate p^{PB}

function in equation (5) into the following form:

$$\pi_{ijt}(r) - \Delta_{it} \cdot \mathbb{1}\{j \neq 0\} - \omega_j, \tag{7}$$

4.3 Price Negotiation

We present the model backwards, starting from the price negotiation following the decision to refinance. The price negotiation process is model as a two-stage game, contingent on i, t, k, and (z_t^m, q_{it}). These notations are all omitted in the following discussion for notational simplicity.

4.3.1 Competitive Stage

We now describe the solution of the negotiation by backward induction, starting with the competition stage. If the borrower rejects the initial offer and starts to search ($S = 1$), the incumbent lender enters into an English auction, competing with other lenders in the market. The competition stage commences with each lender observing an idiosyncratic shock to his lending cost for the borrower, ω_j. We define the effective cost shock $\tilde{\omega}_j = \omega_j + \Delta \mathbb{1}\{j \neq 0\}$ to capture the cost asymmetry, and rewrite equation (7) as $\pi(r) - \tilde{\omega}_j$.

The winning lender, denoted as j^*, is the one with the lowest effective cost shock: $j^* = \arg\min_j \{\tilde{\omega}_j\}$. The probability that lender j wins the auction is given by

$$p_{j^*}^W = \begin{cases} \frac{1}{J \cdot \exp(-\Delta/\sigma_\omega)+1}, \text{ if } j^* = 0 \\ \frac{\exp(-\Delta/\sigma_\omega)}{J \cdot \exp(-\Delta/\sigma)+1}, \text{ if } j^* \neq 0. \end{cases} \tag{8}$$

When $\Delta = 0$, the incumbent wins with the same chance as other lenders, $p_0^W = 1/(J+1)$. When $\Delta > 0$, that is, the incumbent has a cost advantage, the incumbent wins with a higher probability than any competing lender, $p_0^W > 1/(J+1)$, and the incumbent's chance of winning increases with the extent of the advantage Δ.

The winner in the auction charges an interest rate r^C that makes the closest runner-up just break even:

$$r^C = \pi^{-1}\big(\tilde{\omega}_{(2)}\big) \tag{9}$$

where $\tilde{\omega}_{(2)}$ is the runner-up lender's effective cost shock, or the second lowest of all. The distribution of $\tilde{\omega}_{(2)}$ conditional on the winner j^*, denoted as $F_{\tilde{\omega}_{(2)}|j^*}$, has an analytical form with the following conditional expectation (Brannman and Froeb, 2000). The $\tilde{\omega}_{(2)}$ given j^* is:

$$E\big[\tilde{\omega}_{(2)} \,\big|\, j^*\big] = -\sigma_\omega \log\left(J \exp\left(-\Delta/\sigma_\omega\right) + 1\right) - \frac{\sigma_\omega \log(1 - p^W_{j^*})}{p^W_{j^*}}. \tag{10}$$

It follows that the expected competitive offer, denoted as $\bar{r}^C$, is

$$\bar{r}^C = -\frac{\sigma_\omega}{M}\,\pi^{-1}\left(\log(J \exp\left(-\Delta/\sigma_\omega\right) + 1) + \sum_{j^*=0}^{J} \log(1 - p^W_{j^*})\right) \tag{11}$$

Finally, the incumbent's expected profit in the competitive stage is given by:

$$\bar{\pi}^S_0 \equiv E[\pi_0 \,|\, S = 1] = -\sigma_\omega \log(1 - p^W_0), \tag{12}$$

which increases with the incumbent's cost advantage Δ.

4.3.2 Initial Stage and Search Decision

The incumbent lender solves the profit-maximization problem upon receiving an inquiry from a borrower. Given any incumbent's quote r, the borrower chooses to search if the net gain from searching, $\Delta U(r) = U(\bar{r}^C) - U(r) = \alpha(r - \bar{r}^C)$, is greater than the search cost, κ.

$$S = \mathbb{1}\{\kappa < \Delta U(r)\} \tag{13}$$

Letting H denote the distribution function of the search cost, it then follows that the rejection probability is $H\left(\Delta U(r)\right)$. Thus, the incumbent's initial offer comes from the following problem:[28]

$$\max_r (1 - H(\Delta U(r)))\,\pi_0(r) + H(\Delta U(r))\bar{\pi}_0^S. \tag{14}$$

The specification of linear utility function and uniform distribution of search cost transforms the incumbent's problem in equation (14) into a quadratic optimization problem, which has a closed-form solution. Specifically, the initial offer, r^I, is a piecewise linear function:

$$r^I = \begin{cases} \bar{r}^C + \frac{\bar{\kappa}(1-e)}{\alpha}, & \text{if } \hat{r} - \bar{r}^C \leq \frac{\bar{\kappa}(1-3e)}{\alpha}, \\ \frac{1}{2}\left[\hat{r} + \bar{r}^C + \frac{\bar{\kappa}(1+e)}{\alpha}\right], & \text{if } \frac{\bar{\kappa}(1-3e)}{\alpha} < \hat{r} - \bar{r}^C \leq \frac{\bar{\kappa}(1+e)}{\alpha}, \\ \hat{r}, & \text{if } \hat{r} - \bar{r}^C > \frac{\bar{\kappa}(1+e)}{\alpha}. \end{cases} \tag{15}$$

The associated search probability is

$$\Pr(S=1) = \begin{cases} 0, & \text{if } \hat{r} \leq \bar{r}^C + \frac{\bar{\kappa}(1-3e)}{\alpha}, \\ \frac{\alpha\left(\hat{r}-\bar{r}^C\right)}{4\bar{\kappa}e} - \frac{1-3e}{4e}, & \text{if } \bar{r}^C + \frac{\bar{\kappa}(1-3e)}{\alpha} < \hat{r} < \bar{r}^C + \frac{\bar{\kappa}(1+e)}{\alpha}, \\ 1, & \text{if } \hat{r} \geq \bar{r}^C + \frac{\bar{\kappa}(1+e)}{\alpha}, \end{cases} \tag{16}$$

where $\hat{r} = \pi^{-1}(\bar{\pi}_0^S)$ is the incumbent's reservation price. It is the interest rate at which the incumbent lender is indifferent whether the offer is accepted or not, because the expected profits are the same. A borrower's reservation price is $\bar{r}^C + \kappa/\alpha$, which is additive in $\bar{r}^C$. Thus, the term $\hat{r} - \bar{r}^C$ governs the difference in reservation price between the incumbent and the borrower. A lower value of $\hat{r} - \bar{r}^C$ increases the likelihood that the borrower's reservation price exceeds that of the incumbent, thereby increasing the probability of the initial offer being accepted. In essence, $\hat{r} - \bar{r}^C$ serves as a measure of the incumbent's pricing advantage during the initial stage. Depending on the value of $\hat{r} - \bar{r}^C$, the pricing function has different slopes.

When $\hat{r} - \bar{r}^C$ is smaller than the first cutoff, $\frac{\bar{\kappa}(1-3e)}{\alpha}$, the initial offer is flat at $\bar{r}^C + \frac{\bar{\kappa}(1-e)}{\alpha}$.

[28]Note that we normalize the incumbent's cost shock in this stage as zero.

This is the price at which the borrower with the lowest search cost $\bar{\kappa}(1-e)$ is indifferent between searching and not searching. Thus, the offer is accepted with probability 1. Any price lower than it cannot further increase the acceptance probability, and thus it serves as a floor on the initial offer. When $\hat{r}-\bar{r}^C$ falls between the two cutoffs, $\hat{r}-\bar{r}^C \in \left(\frac{\bar{\kappa}(1-3e)}{\alpha}, \frac{\bar{\kappa}(1+e)}{\alpha}\right)$, the initial offer increases with $\hat{r}$ at a slope of 1/2. In this interval, the monopolistic incumbent faces the classic tradeoff between price and demand, and the price is determined by the interior solution to the first-order condition of the profit-maximization problem. The slope of r^I with respect to $\hat{r}$ is analogous to the pass-through rate of marginal cost, which is 1/2 due to the incumbent's monopoly position in this case. The probability of searching changes linearly in $\hat{r}$ from 0 to 1. In the last scenario, $\hat{r}-\bar{r}^C$ is larger than the second cutoff, $\frac{\bar{\kappa}(1+e)}{\alpha}$. At this point, even the borrower with the highest search cost would search, since the net gain from searching outweighs the search cost. Thus, an initial offer in this interval is rejected with probability 1.

An interesting observation is that the incumbent pricing advantage is higher with a smaller number of competing lenders or a smaller dispersion of cost shock. In other words, $\hat{r}-\bar{r}^C$ increases with J and σ_ω, while the effect of Δ is ambiguous.[29] This is because although Δ inflates the expected profit in the competitive stage (from equation 12), it also drives up the expected competitive offer $\bar{r}^C$, so the net effect depends on the comparison of the two opposing forces.

An analysis of the incumbent's market power calls for an examination of the markup. Let $r^b = P_0/M + g + c$ denote the break-even price. Then the incumbent's markup in the initial stage can be decomposed into two parts:

$$r^I - r^b = \underbrace{r^I - \hat{r}}_{\text{Markup from search friction}} + \underbrace{\hat{r} - r^b}_{\text{Markup from cost advantage}} .$$

[29]This can be seen from

$$\hat{r}-\bar{r}^C = \frac{\sigma_\omega}{M}\,\pi^{-1}\big(\log(J\exp(-\Delta/\sigma_\omega)+1\,) + J\log\big(1-(1-P_0^W)/J\big)\big).$$

The first part, $r^I - \hat{r}$, measures how much more the incumbent charges above its reservation price in the first stage. The second part, $\hat{r} - r^b$, measures the difference between its reservation price and the break-even price. Since $\hat{r}$ increases with $\bar{\pi}_0^S$, it therefore increases with the cost advantage Δ. In other words, the incumbent's cost advantage in the competition stage drives up the reservation price it is willing to offer in the initial stage.

To illustrate how the first part of the markup, $r^I - \hat{r}$, arises from search friction, we plot r^I as a function of $\hat{r}$ in Figure 5. The dashed line is at 45 degrees, so the distance between the solid line and the dashed line represents $r^I - \hat{r}$. This markup term is higher with lower values of $\hat{r}$, which means higher pricing advantage.

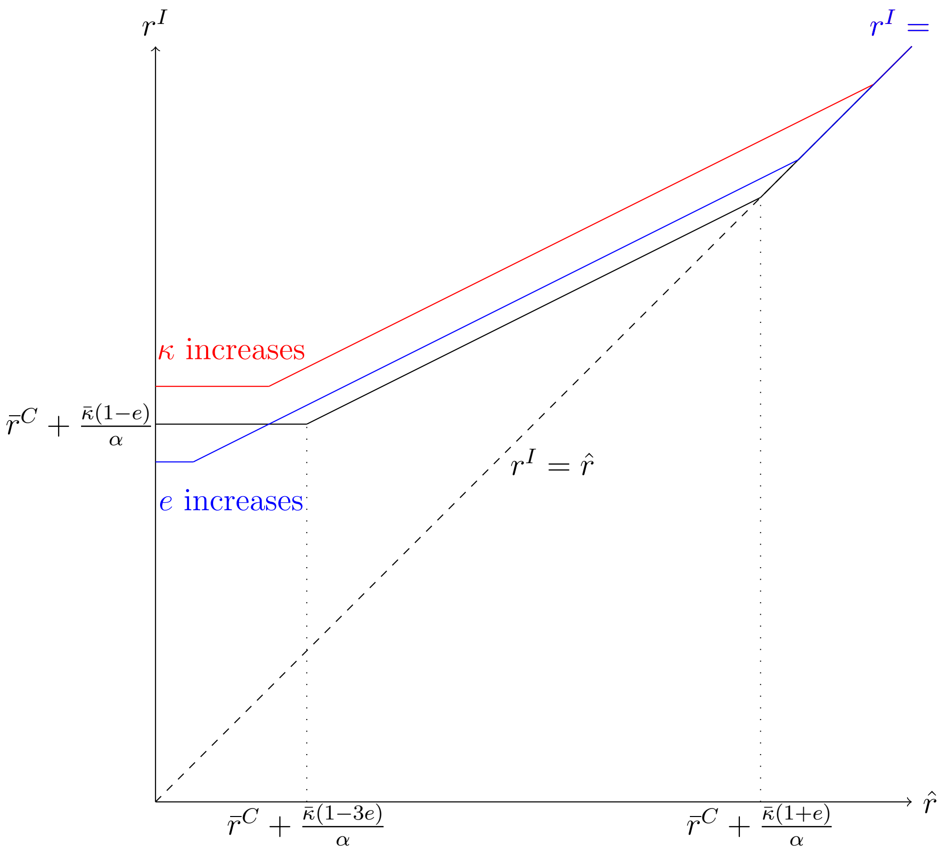


Figure 5: Pricing Function in the Initial Stage

This figure illustrates the initial offer r^I as a function of the reservation price $\hat{r}$, as shown in equation (15). The black solid line is the pricing function at the baseline level. The red solid line shows the pricing function after an increase in κ, and the blue solid line represents the pricing function after an increase in e.

When $\bar{\kappa}$ increases, the pricing function shifts up to the red line, suggesting that the initial quote increases with $\bar{\kappa}$. Intuitively, $\bar{\kappa}$ is the average search cost, and higher average search cost gives the incumbent higher market power in the first stage, thus extracting more surplus.

Interestingly, the effect of e on the initial quote is ambiguous, depending on the value of $\hat{r} - \bar{r}^C$. In the case of a small $\hat{r} - \bar{r}^C$, the incumbent has a high pricing advantage and is able to preempt searching efforts by offering an attractive initial offer. If e goes up in this case, the marginal borrower's search cost, $\bar{\kappa}(1 - e)$, goes up. Therefore, the initial offer required to preempt searching must be lower. On the other hand, this also implies that it is more costly for the incumbent to preempt searching, so the incumbent is more likely to seek an interior solution instead (the middle piece of the pricing function). In this classic scenario of the monopoly pricing problem, a higher e results in a less elastic demand curve, because a 1 percent change in price now leads to less change in demand. Consequently, the optimal price is higher in response to the increasingly inelastic demand.[30]

4.4 Refinancing Decision

Given expected offers from the price negotiation process, we now lay out the borrower's value function and the associated policy function for the refinancing decision. We add back the state variables (z, q) and time subscript t while suppressing borrower index i and refinancing type k.

The ex-ante value of refinance, viewed at the beginning of period t, is the maximum between the expected value of accepting the incumbent's offer and the expected value of searching for competing lenders' offers, net of the fixed cost of refinancing:

$$V_t^{refi}(z, q) = E\big[\max\{U_t(r^I),\ U_t(r^C) - \kappa\}\big] - \phi_t + \mu, \tag{17}$$

where the constant μ reflects the time-invariant utility effect of refinancing, with $\mu > 0$

[30] Similar results hold for the incumbent's expected profit in this stage.

indicating a net benefit and $\mu < 0$ suggesting a net cost. Factors contributing to a positive μ include life-improving opportunities that might come with refinancing in addition to rate reduction, such as moving to a new location with a better labor market match, cashing out for home renovations or debt consolidation, shortening the loan term, or even improving credit scores for borrowers who struggle to make payments. Instead of modeling these channels explicitly, we use μ to summarize their overall effects on refinancing decision.

If the borrower does not refinance in period t, they retain the chance to refinance in the future. The value of waiting is thus the sum of flow utility and the discounted expectation of the continuation value:

$$V_t^{wait}(z,q) = u(y - m^0) + \beta \left[p_t^C EV_{t+1}(z', q') + \left(1 - p_t^C\right) \underline{U}_t\right], \tag{18}$$

where m^0 is the mortgage payment on the original mortgage.

In addition to the factors accounted for V^{wait} and V^{refi}, other idiosyncratic unobserved determinants are summarized in a pair of utility shocks, $(\epsilon_t^0, \epsilon_t^1)$, which are i.i.d. random variables with zero means. The expected value of having a refinancing opportunity in period t is thus given by:[31]

$$V_t(z,q) = \max\left\{V_t^{wait}(z,q) + \epsilon_t^0,\ V_t^{refi}(z,q) + \epsilon_t^1\right\},\ t = 1, ..., T. \tag{19}$$

4.5 GSE and Investor Profits

We introduce the profit functions of the GSEs and MBS investors in this section to complete the model. Here, the GSEs and the investors are not strategic agents. Keep the calculation simple, we assume that each borrower is matched with an investor through the GSEs' secularization, and that the investor funds the borrower's mortgage at $t = 0$ and receives the coupon payment $c_0 L_{i0}$ in each period, where L_{i0} is the original loan size. If the borrower

[31] The terminal value is given by $V_{T+1} = \sum_{\tau=T+1}^{\bar{T}} \beta^{\bar{T}-\tau} u(y,h)$, i.e., the discounted sum of the utility flow of a mortgage-free homeowner until the end of life.

refinances the mortgage at t_i^*, the investor's coupon payment will be updated to $c_{t_i^*} L_{it_i^*}$. Therefore, the investor's total profit is:

$$\Pi_i^M = -L_{i0} + \begin{cases} c_0 L_{i0} T, \text{ if no refinance,} \\ c_0 L_{i0} t_i^* + c_{t_i^*} L_{it_i^*} T, \text{ if refinance at } t_i^*. \end{cases} \tag{20}$$

Investors are protected from credit risks because of the guarantee from the GSEs. The GSEs receive the guarantee fee on the original mortgage $g_{i0} L_{i0}$ from the lender in each period, and in the case of refinancing at t_i^*, the guarantee fee becomes $g_{it_i^*} L_{it_i^*}$, where $g_{it_i^*}$ reflects the new LTV at the time of refinancing. In the case of a mortgage default, the GSEs incurs a loss, given by $Loss_i(T_i^*)$ where $T_i^* <= T$ is the period in which the borrower defaults, or $T_i^* = T + 1$ if default never happens and $Loss_i = 0$.[32] However, the default loss can be ameliorated by the possibility of put-back. We represent this compensation with the product of the put-back probability and loan balance. Specifically, the compensation is $\bar{p}_i^{PB} L_{i0}$ if the mortgages is never refinanced, where $\bar{p}_i^{PB}$ is the put-back probability on the original mortgage. And the compensation is $p_{ij_i^* t_i^*}^{PB} L_{it_i^*}$ in the case of refinancing, where j_i^* is the chosen lender. To sum up, the GSEs' profit is:

$$\Pi_i^G = \begin{cases} g_{i0} T_i^* - Loss_i(T_i^*) + \bar{p}_i^{PB} L_{i0}, \text{ if no refinance,} \\ g_{i0} t_i^* + g_{it_i^*} T_i^* - Loss_i(T_i^*) + p_{ij_i^* t_i^*}^{PB} L_{it_i^*}, \text{ if refinance at } t_i^*. \end{cases} \tag{21}$$

5 Estimation and Identification

We now discuss our method to estimate model primitives. We begin by discussing specifications we make to the model in order to fit the empirical settings. Section 5.1.1 specifies borrowers' beliefs in different time periods, in line with the actual timeline of HARP's roll-out and the policy change regarding mortgage put-back. In Section 5.1.2, we describe methods

[32] Note that T_i^* refers to the age of the refinanced mortgage in the case of refinancing; otherwise it is the age of the original mortgage.

employed for the parameterization of a variety of functions and distributions, as well as off-model estimations of some of the functions. We discuss the sources of identification of model parameters in Section 5.2, and then derive the likelihood function and describe the estimation procedure in Section 5.3.

5.1 Empirical Specifications

5.1.1 Timeline

As mentioned in Section 2, HARP was launched in 2009 followed by several changes to the program rules and the related policy on mortgage put-back. In our empirical model, the launch of HARP and the subsequent modifications to the program, as well as the change in put-back policy, are not foreseeable by a borrower. In addition, the deadline of HARP was extended multiple times throughout its rollout. Table 3 summarizes borrowers' beliefs during the four phases in the empirical model. Section A.2 provides more details.

Table 3: Timeline of the Empirical Model

Year	**HARP Phase**	**Borrower's Belief**	**Put-Back Policy**	**HARP Parameters**
$Y0$–2008	No HARP	No HARP	No change	
2009–2011	HARP 1.0	HARP 1.0 from 2009–2012	No change	$\phi^H = \phi_0$, ξ_1
2012	HARP 2.0	HARP 2.0 from 2012–2013	No change	$\phi^H = 0$, ξ_2
2013–2018	HARP 2.0	HARP 2.0 from 2013–2018	Post-change	$\phi^H = 0$, ξ_2

This table summarizes the timeline of the empirical model. The first column shows the time periods for each of the four phases, where $Y0$ refers to the start year of a borrower's original mortgage. The second column describes the borrower's belief about HARP in each phase, and the third column shows the borrower's belief about the put-back policy in each phase.

5.1.2 Parametrization

We focus on 30-year fixed-rate mortgages, $T = 30$, and set a borrower's life horizon to $\bar{T} = 50$.[33] The discount factor $\beta = 0.95$. Markets are defined by states. The number of competing lenders J is set as a quarter of the total number of lenders in the market, rounded to the nearest integer. We specify the guarantee fee g as a function of the borrower's FICO and LTV, based on the g-fee matrix in the annual report published by GSEs. The distribution of utility shocks to refinancing decisions, $(\epsilon_t^0, \epsilon_t^1)$, are assumed T1EV with mean zero and scale parameter σ_V.

Fixed Cost of Refinancing We specify ϕ_{kt} as:

$$\phi_{kt} = \begin{cases} \phi_0 + 1\% \cdot L_{it} \cdot \mathbb{1}\{LTV_{it} > 80\%\}, \text{ if } k = R \\ \phi_0, \text{ if } k = H \text{ and } year_t \in [2009, 2011] \\ 0, \text{ if } k = H \text{ and } year_t \in [2012, 2018]. \end{cases} \tag{22}$$

Compared to regular refinancing, HARP 1.0 eliminates the cost of private mortgage insurance for those with LTV over 80%, which is approximated by 1% of mortgage balances. HARP 2.0 further eliminates the fixed cost by ϕ_0. This is driven by the streamlined the paperwork and the clarified the rules under HARP 2.0, which could lower the psychological component of ϕ.

Repayment Probability We use a log-logistic survival function to model the probability of non-default until period t: $\left[1 + (\lambda_i t)^{1/s}\right]^{-1}$, where λ_i is parameterized as $\exp(-X_i' b)$ and X_i includes borrower characteristics (FICO and income), original interest rate and LTV, principal, cohort fixed effects, and market fixed effects. Using the monthly performance data on the original mortgages in the sample, we estimate b and s using the maximum

[33] Note that borrowers cannot refinance from $t = 21$ to $t = 30$ because the remaining lifetime is shorter than the mortgage term.

likelihood method, and the results are presented in the Internet Appendix A.1. Using the model estimates, we then calculate p_t^C, the probability of non-default until period $t+1$ conditional on non-default until period t, as

$$p^C = \frac{1 + \left(t\hat{\lambda}\right)^{1/\hat{s}}}{1 + \left((t+1)\hat{\lambda}\right)^{1/\hat{s}}}. \tag{23}$$

The Market-Level House Value Index and the Cost of Funds We use the yearly average coupon rate in the MBS market as the measurement of c_t, which is on the national level. We define market m on the state level, and we use the HPI for each state as the measure of h_t^m. For each $m = 1, ..., 51$, we estimate a VAR(1) process for $(\log(h_t^m), c_t)$ and use a discrete approximation to the VAR(1) process via the method proposed by Farmer and Toda (2017).[34]

Idiosyncratic House Value Shock Given the market-level change in house value, Δh_t^m , we assume that the individual-level change in house value, Δh_{it}, is determined by

$$\log(\Delta h_{it}) = \beta_0 + \beta_1 \log(\Delta h_{it}^m) + q_{it},\ q_{it} \sim N(0, \sigma_q). \tag{24}$$

The conditional distribution of Δh_t given Δh_{it}^m is thus determined by β_0, β_1, and σ_q. Notice that equation (24) can only be estimated for borrowers who refinance under HARP, because the available data include both the original home value and the new home value exclusively for the HARP takers and not for other borrowers. However, this subsample of borrowers with HARP refinances is highly selective, so a direct OLS estimation of equation (24) using this subsample would yield biased results for the whole sample of borrowers. We tackle this problem by applying a two-step Heckman selection model. The first step involves analyzing the choice to opt for HARP refinancing. The set of variables in the first-stage regression that are excluded from the main regression model include borrower characteristics (FICO,

[34] We assume a linear trend for $\log(h_t^m)$ in the VAR(1) estimation.

income, whether first-time home buyer) and loan characteristics (interest rate, principal, LTV, insurance percentage, etc). The Internet Appendix A.4 provides further details of the estimation procedure and results.

Multiplier We impute the multiplier M in a lender's profit function using the predicted mortgage duration based on borrower characteristics. We estimate a log-normal survival model using the monthly performance data on the original mortgages in the sample. Covariates include borrower characteristics (FICO and income), loan characteristics (interest rate, LTV, principal), market fixed effects, and cohort fixed effects. Results are presented in the Internet Appendix A.1.

Put-Back Probability We use the estimated logit model of the put-back probability in Section 3.3.1, $p^{PB}(X_i, t; Incumbent_j, Post_t)$, to approximate p^{PB}_{ijt}, where covariates of the logit regression include borrower characteristics X_i, the duration of the original mortgage (i.e., period t), $Incumbent_j \times (1 - Post_t)$ dummy, and $Post_t$ dummy, where $Incumbent_j = \mathbb{1}\{j = 0\}$ and $Post_t = \mathbb{1}\{year_t \geq 2013\}$. The cost parameter P_{cost} is left for structural estimation. This specification implies that

$$\Delta_P = P_{cost} \cdot \left[p^{PB}(X_i, t; Incumbent_j = 0, Post_t) - p^{PB}(X_i, t; Incumbent_j = 1, Post_t)\right].$$

Note that $\Delta_P = 0$ if $Post_t = 1$ since the interaction term is only present in the pre-2013 period.

5.2 Identification

The set of model parameters to estimate, θ, include: (i) parameters in the search cost distribution: $\bar{\kappa}$, e, (ii) supply-side parameters: P_{cost}, σ_ω, Δ_F, (iii) the relative refinancing cost, ϕ_0, (iv) the fixed utility effect of refinancing, μ, (v) the scale parameter in the distribution of utility shocks to refinancing decisions, σ_V, and (vi) the probability of choosing HARP for qualified borrowers during HARP 1.0 and 2.0, respectively: ξ_1, ξ_2. Table 4 presents the set of parameters and the key identifying moments. Detailed discussion on model identification is in Section A.3.

Table 4: Parameters and Identifying Moments

Supply-side parameters: P_{cost}, σ_ω, Δ_F	Joint distribution of (1) shares of same-lender refinancing and shares of searchers; and (2) competing lenders' prices pre- and post-2013
Search cost distribution: $\bar{\kappa}$, e	Incumbent lenders' prices and share of searchers
Relative refinancing cost: ϕ_0	Changes in refinancing activity after HARP 2.0
Fixed utility effect of refinancing: μ	The overall level of refinancing activity
The scale parameter of utility shocks: σ_V	The cross-sectional variation in refinancing decisions across different markets
HARP Awareness parameters: ξ_1, ξ_2	The relative share of HARP refinancing compared to regular refinancing during HARP 1.0 and HARP 2.0

5.3 Likelihood Function

Let d_t denote the refinance decision of a borrower in period t, where $d_t = 1$ stands for refinancing and $d_t = 0$ otherwise.[35] Conditional on refinancing, we observe the type of refinancing, $k = H$ or R. Conditional on HARP refinancing, we further know whether it is with the incumbent ($j^o = 0$) or another competing lender ($j^o \neq 0$). Therefore, the observed

[35] We interpret all observed prepayment as refinancing activities, although in reality it could also include prepayment for reasons other than refinancing, such as moving.

action of the borrower in period t, denoted as a_t, falls into one of the four cases:[36]

$$a_t = \begin{cases} 0, & \text{if } d_t = 0, \\ 1, & \text{if } d_t = 1, k = H, j^o = 0, \\ 2, & \text{if } d_t = 1, k = H, j^o \neq 0, \\ 3, & \text{if } d_t = 1, k = R. \end{cases} \tag{25}$$

The probability of non-refinance is given by (omitting the state variable (z, q)):

$$\Pr(a_t = 0) = \Pr(d_t = 0) = \frac{1}{1 + \exp\Big(\Big(V_t^{refi} - V_t^{wait}\Big)/\sigma_V\Big)}, \tag{26}$$

Using function $I = \mathbb{1}\{80\% < \text{LTV} < \text{cap}\}$ as an indicator for HARP eligibility, the probability of choosing HARP refinancing with the incumbent can be written as:

$$\begin{aligned} \Pr(a_t = 1) &= \Pr(d_t = 1)\Pr(k = H)\Pr(j^o = 0) \\ &= \xi I \Pr(d_t = 1)\left[\Pr(S = 0) + \Pr(S = 1)\Pr(j^* = 0 \,|\, S = 1)\right]. \end{aligned} \tag{27}$$

Similarly, for the other two cases,

$$\Pr(a_t = 2) = \xi I \Pr(d_t = 1)\Pr(S = 1)\Pr(j^* \neq 0 \,|\, S = 1), \tag{28}$$

$$\Pr(a_t = 3) = (1 - \xi I)\Pr(d_t = 1). \tag{29}$$

Adding back the borrower index $i = 1, ..., N$, the observed outcomes for borrower i, O_i, is the collection of actions and realized macro state variables from the first year after mortgage

[36] This classification is for non-default borrowers. Borrowers who end up in default are not used for likelihood estimation because their likelihood contribution is determined by parameters governing the transition of market-level variables and parameters in the survival model, which do not change with structural parameters.

origination ($t = 1$) to the last year that the borrower appears in the sample, T^i:

$$O_i = \left\{ a_t^{(i)}, z_t^{(i)} \right\}_{t=1}^{T^i}. \tag{30}$$

Note that T^i indicates the year of refinancing if the borrower ever refinances, otherwise it corresponds to the last year of the sample. Given the model parameters θ, the likelihood of the observed outcomes for borrower i conditional on the initial state $z_0^{(i)}$ is:

$$L\left(O_i \,\middle|\, z_0^{(i)}, \theta\right) = \prod_{t=1}^{T^i} \Pr\left(z_t^{(i)} \,\middle|\, z_{t-1}^{(i)}\right) \int \Pr\left(a_t^{(i)} \,\middle|\, z_t^{(i)}, q\right) d\Phi(q/\sigma_q) \tag{31}$$

where $\Phi(\cdot)$ is the standard normal distribution function.

The model also predicts refinancing prices, but these are only observable in the data for HARP refinancing. A natural method is to compute the likelihood of observed prices for HARP borrowers and incorporate this into the likelihood function. Consequently, the likelihood contribution of prices is solely from those opting for HARP refinancing, representing a mere 8.8% of our sample borrowers. The absence of price data for the majority of borrowers significantly constrains the role of price information in the estimation of model parameters, particularly those on the supply side. Despite attempts to use this method, it failed to yield reasonable estimates, leading us to adopt an alternative estimation procedure.

Following Allen et al. (2019), we use a quasi-likelihood estimator that incorporates a set of auxiliary moments in addition to the likelihood function. The set of moments we use, $m(\theta)$, includes four price moments and one aggregate moment on search efforts from an external source, NSMO. The four price moments come from four groups, respectively: (1) HARP refinancing with the incumbent lender prior to 2013, (2) HARP refinancing with the incumbent lender post 2013, (3) HARP refinancing with a competing lender prior to 2013, and (4) HARP refinancing with a competing lender post 2013. For each group, we calculate the expected HARP price from the model and obtain its distance from the sample average. For the aggregate moment on search effort, we use the model to calculate the average search probability for those with either HARP or regular refinancing. The analog probability from the survey is calculated as the fraction of borrowers who search more than one lender when refinancing their mortgage. The difference between the two is a mean-zero error under the null hypothesis that the model is correctly specified. Using the variance of data moments as weighting matrix $\hat{W}$, we construct the following aggregate log likelihood function:[37]

$$\max_{\theta} \sum_{i=1}^{N} \log L\left(O_i \,\middle|\, z_0^{(i)}, \theta\right) - m(\theta)^T \hat{W}^{-1} m(\theta) \tag{32}$$

In our computation of likelihood function in equation (31), the integral over q is numerically approximated. It is important to note that directly drawing from $N(0, \sigma_q)$ is problematic in our setting because it might fail to rationalize some observed HARP refinancing decisions. Specifically, when draws of q are too centered around zero, the predicted LTV can fall below 80% for borrowers that actually choose HARP refinancing, thus being directly rejected by data. To provide enough coverage, we use Halton draws from the an auxiliary distribution (which is also a normal distribution) and use importance sampling to reweight the draws. The auxiliary distribution is chosen to rationalize all observed HARP refinances.

6 Estimation Results

6.1 Parameter Estimates

Table 5 summarizes the parameter estimates, with the standard errors enclosed in parentheses. The monetary values that directly enter the borrower's value functions, including $\bar{\kappa}$, ϕ_0, μ, and σ_V, are expressed in units of \$1,000. Supply-side parameters, including P_{cocst}, σ_ω, and Δ_F, are expressed on a per-hundred-dollar basis of the mortgage.

The search cost is on average \$5,281, ranging from $\$5,281 \times (1 - 0.496) = \$2,662$ to

[37] See Allen et al. (2019) for more discussion on the performance of this estimation approach.

Table 5: Maximum Likelihood Estimation Results

$\bar{\kappa}$	e	ϕ_0	μ	σ_V
5.281	0.496	43.675	53.117	152.016
(0.008)	(0.001)	(0.543)	(0.565)	(0.874)
P_{cost}	σ_ω	Δ_F	ξ_1	ξ_2
969.476	3.880	-0.870	0.385	0.895
(7.789)	(0.009)	(0.003)	(0.003)	(0.006)

The first row of each table shows the estimates of the model parameters, and the second row represents the corresponding standard error for each parameter. $\bar{\kappa}$, ϕ_0, μ, and σ_V are in units of \$1,000, while P_{cocst}, σ_ω, and Δ_F are expressed on a per-hundred-dollar basis of the mortgage.

$\$5,281 \times (1 + 0.496) = \$7,900$. Since this is the search cost over a borrower's lifetime, our estimate is significantly higher than the estimate of average search cost from Allen et al. (2019), where the search costs are expressed over the five-year term of the mortgage contract. Although the search cost estimates are nominally large, they represent on average only 2.67% of total interest cost over the entire horizon of the contracts. This is close to the estimate of 2.5% from Allen et al. (2019).

The parameter ϕ_0 represents the refinancing cost saved by HARP 2.0 compared to HARP 1.0. Recall that one of the changes in HARP 2.0 is waiving the requirement for a traditional home appraisal, which costs about one thousand dollars at most. Our estimate of ϕ_0, \$43,569, is significantly larger than this. This suggests the importance of implicit psychological effects of waiving the appraisal requirement and other changes that streamlined the refinancing process and simplified the rules. This is inline with findings from Stanton (1995) and Andersen et al. (2020), which indicate that psychological refinancing costs play a significant role in refinancing decisions. Our result suggests that HARP 2.0 significantly reduced refinancing costs for borrowers and the majority of the reduction comes from the implicit psychological cost.

Our estimate of μ indicates large benefits from refinancing due to reasons other than rate reduction. This may include the opportunity of moving to a location with better labor market matches, cashing out for home renovations or debt consolidation, shortening the loan term, or even improving credit score if the borrower struggles to meet payments on the exiting mortgage. The overall effect of these factors offsets the fixed cost of refinancing, delivering a net benefit equivalent to about $\mu - \phi_0 = 12,036$ (for HARP 1.0 refinancing and regular refinancing with low LTV).

The seemingly large fixed benefit of refinancing is mostly muted by the large variance of idiosyncratic utility shock to refinancing decisions, σ_V. Given the estimated value of σ_V at \$152,016, a HARP 1.0 borrower who derive the same utility from refinancing and not refinancing other than μ and ϕ_0, i.e., $V^{refi} = V^{wait}$, has a refinancing probability of $1/(1 + \exp(-(\mu - \phi_0)/\sigma_V)) = 0.52$, according to equation (26). In this example, the fixed benefit and cost only increase refinancing probability by 0.02. Therefore, although our estimate of the fixed benefit and cost of refinancing are large, they might not be predominant force driving refinancing decisions given the large σ_V.

On the supply side, we find that a mortgage put-back is highly costly for a mortgage lender, according to the estimate of P_{cost}. Based on this estimate, we calculate the incumbent lender's expected put-back cost, $P_0 = P_{cost} \cdot p^{PB}$. For every \$100 of the mortgage, the pre-2013 expected put-back cost for the incumbent, $P_{0|pre}$, is \$2.976 on average. A competing lender, on the other hand, has an expected put-back cost that is \$4.928 higher than the incumbent, marking a 160% difference. The share of the expected put-back cost in a competing lender's total cost is about 18.8%, compared to 8.3% for the incumbent lenders. The asymmetry in put-back cost before 2013 dwarfs other cost differentials between the competing and incumbent lenders, Δ_F, which is less than \$1 per \$100 mortgage. Therefore, the differential exposure to put-back risk is substantial, and it constitutes the main source of the cost advantage prior to 2013. The policy change in 2013 leads to a dramatic decrease in the expected put-back cost, to an average of \$0.105. It qualitatively changed the role of put-back risk in a lender's profit function, contributing to a lower price observed in the data.

Our estimate of σ_ω implies a standard deviation of \$4.977 ($= 3.88\pi/\sqrt{6}$) for the idiosyncratic cost shock in the competition stage. This has important implications for our understanding of the importance of cost advantage in this market. In the absence of any systematic cost difference (i.e., $\Delta = 0$), our estimate of σ_ω implies that the average difference between $\omega_{(2)}$ and $\omega_{(1)}$ is \$5.379 in a duopoly market and \$4.72 with three lenders. With a systematic cost difference $\Delta = \Delta_P + \Delta_F = 4.928 - 0.87 = 4.058$, the incumbent lender's winning probability in the competition stage is 0.74, compared to 0.26 for the competing lender in a duopoly market. In a market with three lenders, it is 0.59 for the incumbent and 0.21 for the two competing lenders. This suggests that the systematic cost advantage between the incumbent and competing lenders is a more important source of market power than the idiosyncratic cost differences.

Finally, the estimated ξ_1 suggests that during the first phase of HARP, an eligible borrower takes up HARP with a 38.5% chance. This reflects poor borrower knowledge and understanding of HARP, as reported in Federal Housing Finance Agency (2013). The assessment pointed out three potential reasons. First, many borrowers were not aware of the program due to a lack of advertising and information campaigns. Second, borrowers may have heard of the program but confused the program with other government housing programs initiated during that time. Third, many eligible borrowers were under the mistaken impression that they were ineligible for HARP because of a lack of clarity and transparency around the program rules. An important factor contributing to the lack of borrower awareness of the program was borrower outreach. During HARP 1.0, lenders were prohibited from directly soliciting borrowers with HARP refinancing (Federal Housing Finance Agency, 2013). As a result, eligible borrowers may have missed the opportunity to learn about the program through lenders.

During the second phase of HARP, the take-up rate witnessed a significant increase to 89.5%. This increase is closely linked to the implementation of a nationwide public education campaign to improve borrower knowledge of the program. The solicitation guidelines for HARP loans were also revised to increase borrower outreach. Our result suggests that these measures during HARP 2.0 were effective at boosting the take-up rate of HARP.

6.2 Model Fit

This section provides a comparison between the model prediction and the observed data to assess the goodness of fit of the baseline model. We start by simulating the model $Ns = 100$ times for each borrower in the data ($i = 1, ..., 21247$). For each borrower i, we solve the model to find the refinancing probability and eligibility for HARP in each state from $t = 1, ..., T$. Then in each simulation of the borrower, we simulate the default outcome and the path of state variables (z, q) for $t = 1, ..., T$. Based on the simulated path of state variables, we then simulate the refinancing decision. If refinancing occurs, we then draw the refinancing type based on the eligibility for HARP. Next we draw the search type and find the search decision. If searching, we then draw the winner of the competition stage and find the expected price. We also re-calculate the probability of default after refinancing and simulate the default outcome on the refinanced mortgage.

Using the simulated data, we calculate the fraction of borrowers who refinance in each year from 2009 to 2018 and compare this with the fraction calculated from the data, as depicted in Figure 6a. Although the model struggles to match the high refinancing uptake in 2009, it successfully mirrors the overall downward trend of refinancing activities, particularly the sharp decline after 2012. There are at least two reasons for the decline in refinancing rate after its peak in 2012. One reason is that significant enhancements to HARP was enacted in 2012, which increased the awareness and attraction of HARP. Many HARP borrowers therefore refinanced in that year without knowing the upcoming policy revisions to put-back risk. Second, borrowers' LTV ratios declined over time as the housing market recovered, and those who hasd already taken HARP were not allowed to take the program again. So the pool of eligible borrowers shrank over time.

We then compare the refinancing rate for HARP, focusing on a subsample of borrowers with initial LTVs over 80%. This subset of borrowers is more prone to distress, making

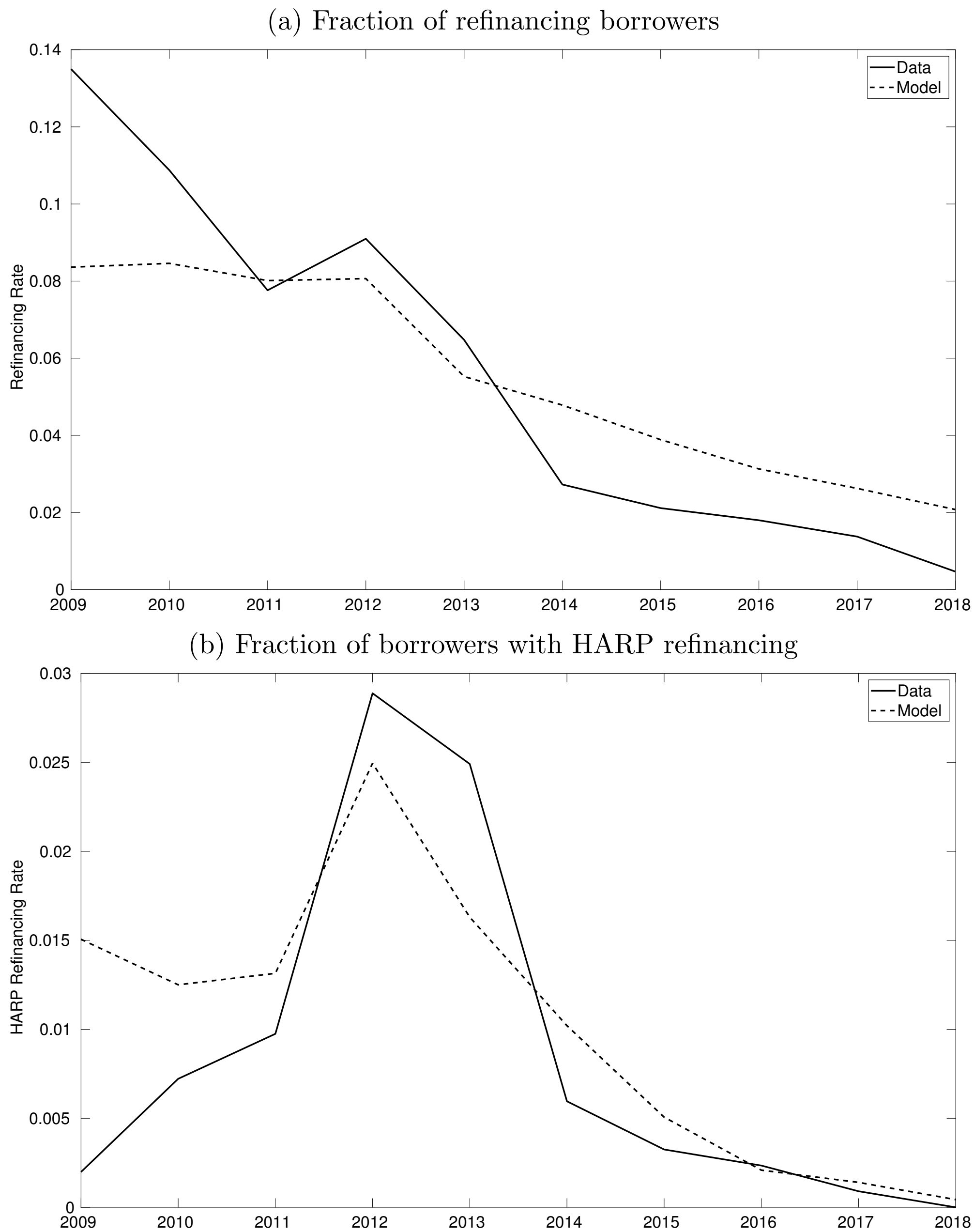


Figure 6: Model Fit

This figure shows the model predictions of refinancing decisions compared with the data. Panel (a) shows the fraction of refinancing borrowers in each year from 2009 to 2018, calculated as the number of borrowers who refinanced in a given year divided by the total number of borrowers. Panel (b) shows the fraction of borrowers with HARP refinancing among those whose initial LTV of the previous mortgage exceeded 80%. Within this subsample, the fraction is calculated as the number of borrowers choosing HARP refinancing in a given year divided by the total number of borrowers in the subsample.

them the prime target for the program. The HARP refinancing rate is calculated by dividing the number of borrowers who opt for HARP refinancing each year by the total number of borrowers in the subsample. Figure 6b shows the comparison between the model prediction and the actual data. The model's prediction of HARP refinancing rate is higher than the data in 2009. Nevertheless, the model accurately captures the significant uptake of HARP since 2012 and the program's gradual decline during its latter half.

The average pre-2013 interest rate on HARP refinancing in the simulated data is 4.95%, compared to 4.51% in the data. In the post-2013 period, the model predicts an average interest rate of 4.28% for HARP refinancing compared to 4.11% in the data. About 51% of borrowers search when refinancing, close to the 49% from the NSMO survey. Among searchers, about 39% still choose the incumbent in the competition stage.

7 Counterfactual

Given the estimated model parameters, we conduct a series of counterfactual exercises to evaluate the effect of the put-back policy on the welfare of borrowers, GSEs and investors. In Section 7.1, we decompose the put-back policy change into two parts—a removal of asymmetric risk and a general reduction—and compare their welfare effects. In Section 7.2 we compare the welfare effect of the asymmetric risk exposure with that of the search friction and further explore the interaction between search friction and cost advantage. Additionally, Section A.5 examines the effects of HARP 2.0 modifications in comparison with the welfare effect of the asymmetric risk exposure. .

7.1 The Effect of Asymmetric Put-Back Risk

7.1.1 Welfare Effects for Borrowers

The asymmetry between the incumbent and competing lenders in their put-back risk exposure was removed by the new policy in 2013. In addition, the new policy also led to a general

Table 6: Summary of Effects on Borrowers

	Baseline	Sym. risk	Sym. risk + Risk reduction
	(1)	(2)	(3)
Refinancing rate (%)			
All	86.3	86.6	86.9
HARP	6.4	6.4	6.4
Default rate (%)			
All	7.9	7.9	7.8
HARP borrowers	6.1	6.3	6.5
For HARP borrowers:			
Δr (bps)	82.5	123.1	160.9
Δ annual payment	2.3	2.8	3.3
Total payments	207.9	200.3	193.2
Borrower welfare			
All	511.1	513.2	515.1
HARP borrowers	557.6	560.9	564.0

This table summarizes the means of borrower outcome variables from counterfactual scenarios (columns (2) and (3)) and the baseline model (column (1)). Column (1) shows the baseline scenario with the policy change in 2013. Column (2) assumes a partial implementation of the new policy in 2009 with a symmetric exposure to put-back risk for the incumbent and competing lenders. Column (3) assumes a full implementation of the new policy in 2009, with both symmetric exposure and general reduction in put-back risk. Refinancing rate (all) is the percentage of borrowers who refinance before 2018. HARP refinancing rate is the fraction of HARP borrowers. Default rate is measured by the percentage of borrowers who default on their mortgage within 10 years of loan origination. Borrower welfare is the discounted sum of lifetime consumption in units of \$1,000. Δr is the the difference between the original interest rate and the new interest rate on the refinanced mortgage in basis points. Δ annual payment is the difference between the original annual mortgage payment and the new annual payment in units of \$1,000. Total payments is the discounted sum of all mortgage payments throughout the borrower's life with a discount factor of 0.95. $N = 2124700$.

reduction in the put-back risk for every lender. In this section, we first consider the case where the risk exposure is symmetric from the beginning of HARP but the general reduction happens later in 2013. Then we consider the case where both the symmetric risk exposure and the general reduction occurs from the beginning. Specifically, in the first exercise we set $\Delta_P = 0$ if $year_t \geq 2009$. The incumbent's expected put-back cost remains the same as the baseline model, while competing lenders now have a lower expected put-back cost due to the removal of differential risk exposure. In this setting, the incumbent lender has only the first-mover advantage but not a cost advantage. This is referred to as the symmetric risk case. In the second exercise, we move the policy change from 2013 to 2009, which is referred to as the full reduction case.

Columns (2) and (3) in Table 6 summarize borrower outcome variables for the two counterfactual exercises. On the extensive margin, we calculate the overall refinancing rate as the number of borrowers who refinance before 2018 divided by the total number of borrowers. The refinancing rate increases from 86.3% to 86.6% in the case of symmetric risk exposure, and it further increases to 86.9% with a full reduction in put-back risk. Interestingly, the HARP refinancing rate hardly changes. In other words, the change in put-back policy leads to more regular refinancing activity rather than HARP refinancing, although the effect is small in magnitude. To assess the effect of the program on loan default, we calculate the 10-year default rate as the fraction of borrowers who default on their mortgage within 10 years of the loan origination. This includes both those who refinance and those who never refinance. Compared with the baseline model, there is hardly any change in the 10-year default rate with the case of symmetric risk exposure. With the full reduction case, the decline is 0.1 percentage points relative to the baseline model.

The subgroup of borrowers with HARP refinancing in the baseline model is particularly interesting. These borrowers generally have a lower default rate, which is consistent with the fact that HARP requires good credit history to qualify and therefore default risk for HARP borrowers are generally lower. Notably, the default rate increases from the baseline case to the case of symmetric risk and the case of full reduction. As we will discuss later, this is possibly due to a larger loan balance at the time of refinancing.

For HARP borrowers, the interest savings from the counterfactual put-back policy is economically significant. With the symmetric exposure case, the average rate reduction through refinancing increases by 40.6 bps (123.1 − 82.5). The rate reduction increases by another 37.8 bps (160.9 − 123.1) with the full reduction in put-back risk. This translates into a reduction in annual mortgage payments by \$0.5K (2.8 − 2.3) and \$0.5K (3.3 − 2.8), respectively. Accounting for the amortization period, the present value of total mortgage payments over a borrower's lifetime decreases by \$7.6K (207.9 − 200.3) on average as the cost asymmetry is removed, with an additional decrease of \$7.1K (200.3 − 193.2) with the general reduction in put-back risk.

To measure borrower's welfare, we calculate the discounted sum of lifetime consumption, taking into account any default outcomes and refinancing activities. The overall borrower welfare increases by \$2.1K (513.2 − 511.1), or 0.4%, with the elimination of the asymmetric risk exposure alone. The welfare gain for HARP borrowers is larger, with an average of \$3.3K (560.9 − 557.6), or 0.6%. The welfare gains almost double with the full installation of the new policy in 2009.

When the policy is introduced in 2009 instead of 2013, most of the welfare change comes from whose who refinance before 2013 in the baseline model, since their refinances now benefit from the earlier implementation of the new policy. It is less obvious that there can also be welfare gains for borrowers who refinance after the change in the baseline model. We find that 3.8% of them would choose to refinance earlier if the new policy is introduced in 2009, with an average of a four-year difference in the timing. With higher-than-average initial LTVs and loan balances, they are more eager to refinance.

For the subgroup of borrowers with HARP refinances before 2013 in the baseline, their average welfare gain is \$5.5K with an earlier introduction of the new policy, which mostly comes from higher interest savings. Given the welfare effect of the new policy on the pre-change sub-sample, it is natural to ask: Does the new policy have the same welfare effect on the post-change sub-sample? To see this, we need to find the welfare loss for post-change HARP borrowers if the policy was never changed. In the counterfactual of no policy change, those with HARP refinances post the change in the baseline have an average welfare loss of \$30.5K compared to the baseline level. This is over five times larger than the effect on the pre-change sample. This large welfare effect can be attributed to three channels: extensive margin, refinance timing, and interest cost. On the extensive margin, 3.42% of the borrowers in this sub-sample would choose not to refinance at all in the counterfactual because the potential benefit of refinance is too low to justify the cost. Among those who still refinance, 12% would refinance later in the counterfactual than in the baseline, with an average of 3.9 years in difference. This leads to longer total amortization period, adding to total mortgage cost. For those whose refinancing timing do not change, their total mortgage payments would increase by 22.9% due to higher interest rate. Overall, the introduction of policy change significantly benefited post-2013 HARP borrowers, although these beneficiaries only make up 30% of total HARP borrowers.

Effects on the Intensive Margin Table 7 focuses on the subsample of borrowers who refinance, especially those with HARP refinancing. In the baseline model, HARP borrowers are significantly riskier than other borrowers who refinance, with a larger initial loan balance and LTV. The average initial loan balance and LTV become larger in the counterfactual scenarios, for both HARP borrowers and other borrowers who refinance. This suggests that the increase in overall financing activity in the counterfactual scenarios are driven by higher-risk borrowers.

How does the timing of refinancing change in the counterfactual scenarios? Figure 7a and 7b plot the refinancing rate and HARP refinancing rate during 2009–2018 in the baseline and counterfactual scenarios. Compared to the baseline model, the overall refinancing rate becomes more front-loaded in the counterfactual scenarios, with higher a refinancing rate

Table 7: Refinancing Outcomes for Refinancing Borrowers and HARP Borrowers

	Baseline		Sym. risk		Sym. risk + Risk reduction	
	All refi (1)	HARP (2)	All refi (3)	HARP (4)	All refi (5)	HARP (6)
At origination:						
Loan balance	171.1	187.4	171.2	186.9	171.2	186.5
LTV (%)	77.8	84.6	77.9	84.6	77.9	84.6
Default risk (%)	9.0	16.3	9.1	16.4	9.2	16.4
At the time of refinancing:						
Δ%loan balance	-10.8	-10.0	-10.7	-9.9	-10.6	-9.8
Δ LTV	-13.9	10.6	-13.8	10.5	-13.6	10.4
Housing shock (%)	0.3	-12.8	0.3	-12.7	0.3	-12.6
Δ default risk	-5.2	-10.3	-5.2	-10.2	-5.3	-10.1
Total payments	203.0	207.9	199.8	200.3	196.9	193.2
N	1985972	136003	1989461	135591	1992429	135163

This table is generated from the subsample of borrowers who refinance and the subsample of borrowers with HARP refinancing under each scenario. Loan balance, reduction in annual payment, total mortgage payments, and borrower welfare are in units of \$1,000. Change in loan balance at the time of refinancing is expressed as the percentage change since loan origination. Change in LTV is the difference between LTV at the time of refinancing and origination. Idiosyncratic housing risk is calculated as $e^q - 1$, where q is the idiosyncratic housing shock variable at the time of refinancing. Change in default risk is the difference between the new 10-year default rate after refinancing and the 10-year default rate without refinancing. Total mortgage payments is the discounted sum of all mortgage payments throughout the borrower's lifetime.

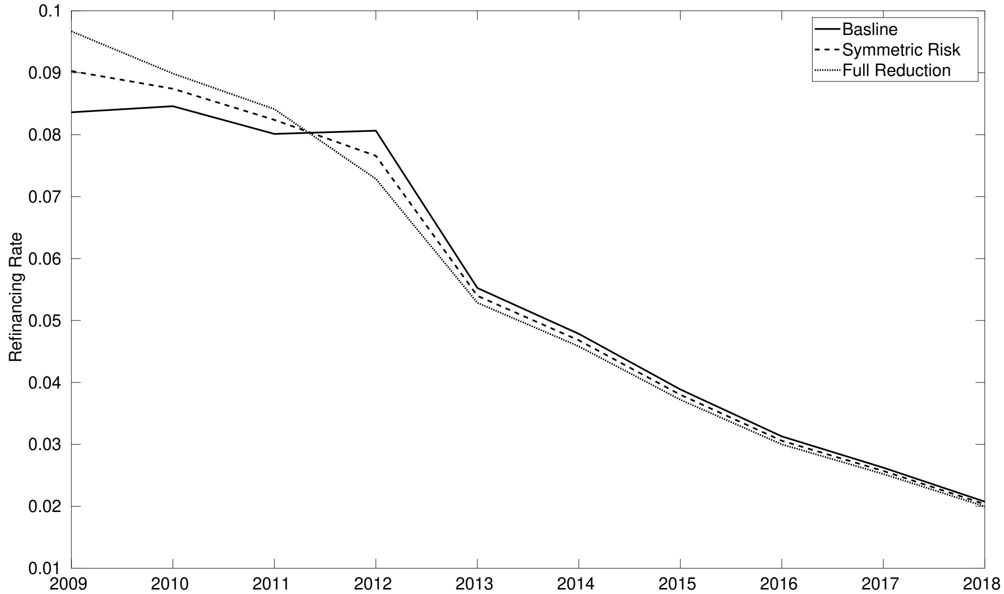
before 2012 and a lower refinancing rate afterward. A similar pattern is also present with the HARP refinancing rate. In other words, some borrowers who refinance later in the baseline model would refinance earlier in the counterfactual scenarios with less waiting time. This is also reflected by the change in loan balance at refinancing from Table 7. In the baseline model, borrowers who refinance typically wait until the loan balance drops by 10.8% before refinancing, while in the counterfactual scenarios the average decreases in loan balance are 10.7% and 10.6%, respectively. The same pattern is shown in the subsample of HARP borrowers.

In general, borrowers who refinance do so when their LTV decreases by 13.9% from origination. However, for HARP borrowers, their LTV at the time of refinancing is typically higher than the initial condition by an average of 10.6% in the baseline model. This is due to their adversarial individual housing condition: On average, their house price is 12.8% lower than the market average. In the counterfactual scenarios, a HARP borrower's LTV is still higher than their initial LTV, but the difference is slightly smaller compared to the baseline model.

The effect of refinancing on default risk is also divergent between HARP borrowers and other borrowers who refinance. For borrowers who refinance, their default risk of the new mortgage is generally lower, and the reduction is slightly larger in the counterfactual scenarios. For HARP borrowers, the risk reduction effect is twice as large (10.3% versus 5.2%), but becomes smaller in the counterfactual scenarios (10.1% versus 10.3%). This can be explained by the relatively larger loan balance at the time of refinancing in the counterfactual scenarios compared to the baseline.

The total mortgage payments for HARP borrowers decrease more with the removal of cost asymmetry than other borrowers. HARP borrowers' total mortgage payments decrease by $7,600 with the removal of cost asymmetry, with an additional $7,100 reduction with the reduction in put-back risk. These effects are twice as large for the average borrower with refinancing activities.

(a) Fraction of refinancing borrowers



(b) Fraction of borrowers with HARP refinancing

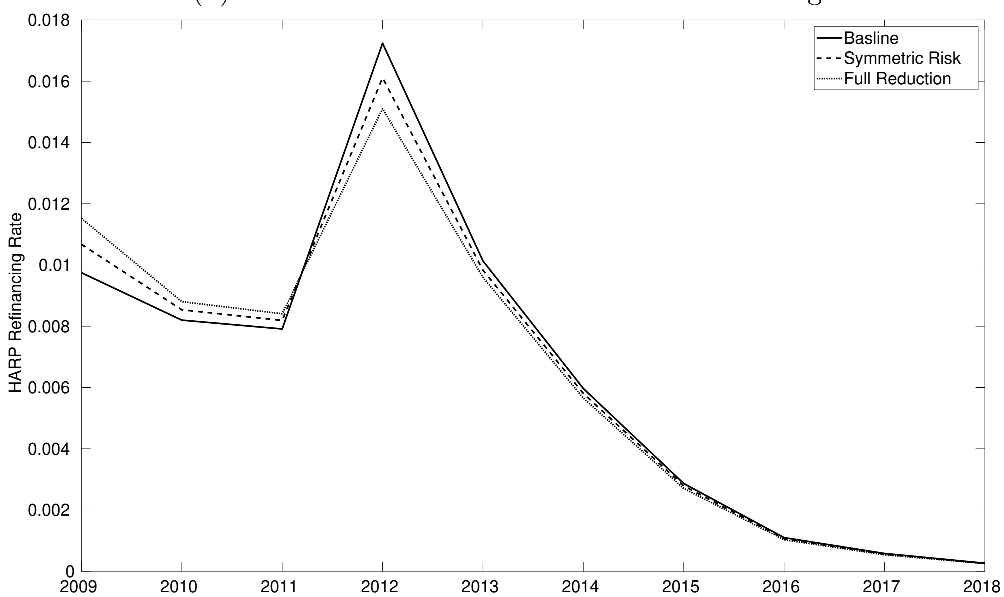


Figure 7: Timing of Refinancing Decisions from the Baseline and Counterfactual Models

This figure shows refinancing decisions from the baseline model and two counterfactual models. The solid line corresponds to the baseline model, the dashed line corresponds to the counterfactual model with symmetric exposure to put-back risk, and the dotted line corresponds to the counterfactual model with a full reduction in put-back risk. Panel (a) shows the fraction of refinancing borrowers in each year from 2009 to 2018, calculated as the number of borrowers who refinance in a given year divided by the total number of borrowers. Panel (b) shows the fraction of borrowers with HARP refinancing.

7.1.2 Welfare Effects for GSEs and Investors

Table 8: Summary of Effects on GSEs and Investors

	Baseline	Sym. risk	Sym. risk + Risk reduction
	(1)	(2)	(3)
GSE Profits			
All	105.6	105.7	105.7
Refinancing borrowers	110.5	110.5	110.5
Non-refinancing borrowers	34.7	34.4	34.2
Investor Profits			
All	168.4	168.5	168.6
Refinancing borrowers	167.3	167.5	167.7
Non-refinancing borrowers	184.5	183.3	182.3

This table summarizes the average profits of GSEs and investors across all borrowers and by subgroups of refinancing and non-refinancing borrowers in each scenario. See Table 6 for definition of scenarios. Profits of GSEs and investors are calculated from equation (21) and (20), respectively, and are shown in units of $1,000.

We summarize the effects of the put-back policy change on GSEs and investors by comparing their profits in the baseline and counterfactual scenarios. Table 8 shows the average profits for all borrowers, as well as for the refinancing and non-refinancing subgroups. Overall, GSE profits increase marginally with the policy change. However, the average profits among refinancing borrowers remain relatively unchanged, while the average profits among non-refinancing borrowers decrease. This suggests that the overall profit increase is driven by the extensive margin of higher refinancing rate, as refinancing borrowers generate significantly higher profits for GSE than non-refinancing borrowers. This is because refinancing extends the period over which the guarantee fee income is generated, and the guarantee fee may also go up if the borrower refinances at a higher LTV. The rise in fee revenues from increased refinancing activities outweighs the decline in put-back compensation, leading to a net increase in overall GSE profits.

The policy change also leads to a slight increase in investor's profits. This increase is primarily driven by the intensive margin of refinancing borrowers, while the average profits from non-refinancing borrowers decline.[38] Unlike the case of GSEs, the extensive margin of higher refinancing rate does not explain the overall profit increase for investors, because their profits from refinancing borrowers are lower than from non-refinancing borrowers. This is because borrowers choose refinancing when interest rates are lower, which means lower monthly payments to investors. However, in the counterfactual scenarios, refinancing occurs earlier than in the baseline model. Given the downward trend in coupon rates over the sample period, earlier refinancing implies a higher coupon rate and higher returns. This effect offsets the negative impact of increased refinancing activities, resulting in higher profits for investors in the counterfactual scenarios compared to the baseline.

Summary of Results In sum, we find that if the new policy on mortgage put-back were implemented in 2009 instead of 2013, 0.6 percentage points more borrowers would have refinanced before 2018, and the timing of refinancing decisions would be earlier. Although HARP take-up rate hardly change compared to the baseline, HARP borrowers benefit more from the program due to a 7.1% decrease in total mortgage payments over their lifetime. Eliminating the incumbent-competing differential in put-back risk alone can achieve about half of the total benefits. This is despite the fact that the marginal effect of the incumbent-competing differential on put-back probabilities is only less than half of the general reduction, as we find in Section 3.3.1. Although GSEs receive less put-back compensation from the policy change, their overall profits do not decline because increased refinancing activities boost guarantee fee revenues. Investors, on the other hand, benefit slightly from the intensive margin of earlier refinancing. Although refinancing generally reduces investor profits by lowering coupon payments, the policy change causes refinancing to occur earlier, when interest rates are generally higher than later in the sample period.

[38]The decline in profits from non-refinancing borrowers is due to a selection effect. In the counterfactual scenarios, more borrowers with higher loan balances choose to refinance. Consequently, the average loan size for non-refinancing borrowers is smaller, leading to a lower investor profits, as these are proportional to the loan size.

7.2 Search Friction and Cost Advantage

Table 9: Mean of Outcome Variables from Counterfactual and Baseline Models

	Baseline (1)	No search friction (2)	Sym. risk (3)	No search friction + Sym. risk (4)
Refinancing rate (%)				
All	86.3	86.6	86.6	86.9
HARP	6.4	6.4	6.4	6.4
Default rate (%)				
All	7.9	7.9	7.9	7.9
HARP borrowers	6.1	6.1	6.3	6.4
For HARP borrowers:				
Δr (bps)	82.5	104.2	123.1	141.8
Δ annual payment	2.3	2.5	2.8	3.0
Total payments	207.9	205.7	200.3	198.6
Borrower welfare				
All	511.1	512.6	513.2	514.5
HARP borrowers	557.6	558.6	560.9	561.7

This table summarizes the means of outcome variables from the counterfactual scenarios (columns (2)–(4)) and the baseline model (column (1)). Column (2) assumes no search friction in the counterfactual scenario. Column (3) assumes symmetric exposure to put-back risk since 2009. Column (4) assumes no search friction and symmetric exposure. The definition of the variables is the same as in Table 6. $N = 2124700$.

The asymmetric put-back risk exposure leads to welfare loss not just because of higher average cost, but more importantly the competitive frictions associated with it. Our results also show considerate search friction in this market, in which the incumbent lenders have a first-mover advantage. How does the first-mover advantage interact with the cost advantage? Does one exacerbate the other? We conduct two additional counterfactual experiments to answer these questions.

The first counterfactual experiment shuts down the search friction by removing the incumbent lender's first-mover advantage. In this case, interest rates are generated directly from an English auction where lenders have potentially heterogeneous costs. Column (2) of Table 9 summarizes borrower outcomes from this experiment. Search friction hardly changes

Table 10: Summary of Effects on GSEs and Investors

	Baseline (1)	No search friction (2)	Sym. risk (3)	No search friction + Sym. risk (4)
GSE Profits				
All	105.6	105.7	105.7	105.8
Refinancing borrowers	110.5	110.6	110.5	110.6
Non-refinancing borrowers	34.7	34.0	34.4	33.7
Investor Profits				
All	168.4	168.3	168.5	168.4
Refinancing borrowers	167.3	167.2	167.5	167.4
Non-refinancing borrowers	184.5	184.6	183.3	183.4

This table summarizes the average profits of GSEs and investors across all borrowers and by subgroups of refinancing and non-refinancing borrowers in each scenario. See Table 9 for definition of scenarios. Profits of GSEs and investors are calculated from equation (21) and (20), respectively, and are shown in units of $1,000.

the extensive margin or default rate, but its effects on the intensive margin is economically significant. For borrowers who refinance, the absence of search friction boosts interest savings by about 13.3 bps, or $200 in annual mortgage payments. Over a borrower's lifetime, it helps to save $1,800 on mortgage payments in terms of present value. Overall, borrower welfare increases by $1,500 in the absence of search cost, which is smaller than the welfare increase associated with the removal of asymmetric risk exposure.

Column (2) in Table 10 shows profits for GSEs and investors in the scenario without search friction. For GSEs, there is a slight increase in average profits, similar to the effect observed when asymmetric risk is removed, as in Column (3). However, the profit composition differs between the two scenarios. In the absence of search friction, refinancing borrowers contribute more significantly to the overall profits compared to the symmetric risk scenario. This difference arises due to the selection effect, where the characteristics of refinancing borrowers vary between the two cases. Eliminating search friction encourages borrowers with lower initial loan balances to refinance, while removing asymmetric put-back risk incentivize borrowers with higher initial balances to refinance. Borrowers with lower loan balances who refinance tend to have lower default risks, thereby extending the time period over which guarantee fees are collected. Conversely, non-refinancing borrowers in this scenario have higher average balances and default probabilities, leading to a decline in average fee revenue due to shorter fee-generating periods and increased credit losses for GSEs. This explains the reduced GSE profits from non-refinancing borrowers observed in Column (2).

Investors, on the other hand, see a slight reduction in profits in the absence of search friction. This reduction is driven by refinancing borrowers. Due to the aforementioned selection effect, refinancing borrowers have lower initial loan balances on average, resulting in lower coupon payments, which are proportional to the loan size.

Column (4) in Table 9 presents the counterfactual experiment in which either search friction and risk asymmetry are present. The extensive margin increase is 0.6 percentage points, with a 0.1 percentage point reduction in default risks for high-LTV borrowers compared to the baseline model. On the intensive margin, the average interest savings of this case is double that of the previous case with no search friction. The overall welfare effect is $3,400, with a higher effect for high-LTV borrowers at $4,200.

By comparing column (4) with column (2), we find that the welfare implication of the risk asymmetry in absence of search friction is $1,900, lower than the welfare effect in an environment with search friction. In other words, the presence of search friction exacerbated the welfare loss from the risk asymmetry. Notice that the opposite is also true. The risk asymmetry also aggravates the inefficiencies from search friction. Therefore, the overall market power of the incumbent is not a simple sum of the two sources; they interact and amplify the individual effects.

8 Conclusion

This paper quantifies the welfare implications associated with the incumbent cost advantage stemming from post-crisis put-back policies. Originally intended as a safeguard against agency frictions in mortgage securitization, put-back provisions inadvertently reinforced incumbent lenders' market power in refinancing. This asymmetry restricted competition and reduced borrowers' opportunities for savings. Our analysis indicates that had this policy distortion been corrected earlier, the welfare gains would have been comparable to those achieved by eliminating search frictionsanother well-documented inefficiency in the mortgage refinancing market.

The results highlight the importance of addressing both structural and policy-driven frictions to improve refinancing outcomes. While structural frictions, such as search costs, are persistent and difficult to eliminate, policy-driven frictions can often be mitigated through regulatory adjustments and greater transparency. Policies that directly impact market participants should be carefully evaluated to ensure they do not create unintended competitive advantages. If certain groups benefit disproportionately, they may extract rents rather than passing cost savings on to borrowers. By ensuring a more level playing field, policymakers can promote competition and improve overall market efficiency, which may have a first-order effect on borrower welfare.

References

Adelino, M., Frame, W. S., and Gerardi, K. (2017). The effect of large investors on asset quality: Evidence from subprime mortgage securities. *Journal of Monetary Economics*, 87:34–51.

Agarwal, S., Amromin, G., Chomsisengphet, S., Landvoigt, T., Piskorski, T., Seru, A., and Yao, V. (2023). Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinance program. *The Review of Economic Studies*, 90(2):499–537.

Agarwal, S., Driscoll, J. C., and Laibson, D. I. (2013). Optimal mortgage refinancing: a closed-form solution. *Journal of Money, Credit and Banking*, 45(4):591–622.

Agarwal, S., Grigsby, J., Hortaçsu, A., Matvos, G., Seru, A., and Yao, V. (2020). Searching for approval. Technical report, National Bureau of Economic Research.

Agarwal, S., Rosen, R. J., and Yao, V. (2016). Why do borrowers make mortgage refinancing mistakes? *Management Science*, 62(12):3494–3509.

Allen, J., Clark, R., and Houde, J.-F. (2019). Search frictions and market power in negotiated-price markets. *Journal of Political Economy*, 127(4):1550–1598.

Allen, J. and Li, S. (2025). Dynamic competition in negotiated price markets. *The Journal of Finance*, 80(1):561–614.

Ambokar, S. and Samaee, K. (2019). Inaction, search costs, and market power in the US mortgage market.

Andersen, S., Campbell, J. Y., Nielsen, K. M., and Ramadorai, T. (2020). Sources of inaction in household finance: Evidence from the danish mortgage market. *American Economic Review*, 110(10):3184–3230.

Arcidiacono, P. and Miller, R. A. (2011). Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity. *Econometrica*, 79(6):1823–1867.

Begley, T. A. and Purnanandam, A. (2017). Design of financial securities: Empirical evidence from private-label rmbs deals. *The Review of Financial Studies*, 30(1):120–161.

Berger, D. W., Milbradt, K., Tourre, F., and Vavra, J. S. (2024). Optimal mortgage refinancing with inattention. Technical report, National Bureau of Economic Research.

Brannman, L. and Froeb, L. M. (2000). Mergers, cartels, set-asides, and bidding preferences in asymmetric oral auctions. *Review of Economics and Statistics*, 82(2):283–290.

Byrne, S., Devine, K., King, M., McCarthy, Y., and Palmer, C. (2023). The last mile of monetary policy: Inattention, reminders, and the refinancing channel. Technical report, National Bureau of Economic Research.

DeFusco, A. A. and Mondragon, J. (2020). No job, no money, no refi: Frictions to refinancing in a recession. *The Journal of Finance*, 75(5):2327–2376.

Demiroglu, C. and James, C. (2012). How important is having skin in the game? originator-sponsor affiliation and losses on mortgage-backed securities. *The Review of Financial Studies*, 25(11):3217–3258.

Farmer, L. E. and Toda, A. A. (2017). Discretizing nonlinear, non-Gaussian Markov processes with exact conditional moments. *Quantitative Economics*, 8(2):651–683.

Federal Housing Finance Agency (2013). Home affordable refinance program: A mid-program assessment. Technical report, Federal Housing Finance Agency.

Federal Housing Finance Agency (2014). Fhfas representation and warranty framework. Technical report, Federal Housing Finance Agency.

Federal Housing Finance Agency (2019). Fannie mae and freddie mac single-family guarantee fees in 2018. Technical report, Federal Housing Finance Agency.

Federal Housing Finance Agency, O. o. I. G. (2013). Home affordable refinance program: A mid-program assessment, fhfaoig.gov/content/files/evl-2013-006.pdf.

Frame, W. S. (2018). Agency conflicts in residential mortgage securitization: What does the empirical literature tell us? *Journal of Financial Research*, 41(2):237–251.

Fuster, A., Goodman, L. S., Lucca, D. O., Madar, L., Molloy, L., and Willen, P. (2013). The rising gap between primary and secondary mortgage rates. *Economic Policy Review*, 19(2).

Goodman, L. (2011). Topic: The obama administration's response to the housing crisis," testimony to the u.s. house of representatives, committee on financial services, http://financialservices.house.gov/uploadedfiles/100611goodman.pdf.

Goodman, L., Seidman, E., and Zhu, J. (2013). Sunset provisions on reps and warrants: Can they be more flexible while still protecting the gses? *Washington, DC: Urban Institute*.

Goodman, L., Zhu, J., and Bai, B. (2015). The impact of early efforts to clarify mortgage repurchases.

Honka, E. (2014). Quantifying search and switching costs in the US auto insurance industry. *The RAND Journal of Economics*, 45(4):847–884.

Keys, B. J., Pope, D. G., and Pope, J. C. (2016). Failure to refinance. *Journal of Financial Economics*, 122(3):482–499.

Scharfstein, D. and Sunderam, A. (2016). Market power in mortgage lending and the transmission of monetary policy. *Unpublished working paper. Harvard University*.

Stanton, R. (1995). Rational prepayment and the valuation of mortgage-backed securities. *The Review of Financial Studies*, 8(3):677–708.

Woodward, S. E. and Hall, R. E. (2012). Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. *American Economic Review*, 102(7):3249–3276.

Internet Appendix

A.1 Survival Analysis

Table 11: Survival Analysis

	(1)	(2)
Exit Event:	Default	Default or Prepay
Model:	Log-logistic	Log-normal
FICO	0.003***	−0.000***
	(0.000)	(0.000)
LTV	−0.014***	0.003***
	(0.000)	(0.000)
Interest Rate	−0.316***	−0.328***
	(0.004)	(0.002)
log(Balance)	−0.308***	−0.254***
	(0.005)	(0.002)
log(Income)	0.182***	0.013***
	(0.004)	(0.001)
Market FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,079,763	2,079,763

Column (1) reports the results of survival probability where the exit event is default using a log-logistic model, while column (2) reports the results of survival probability where the exit event is either default or prepay using a log-normal model. The figures in parentheses are standard errors, with 1, 2, and 3 asterisks indicating statistical significance at 10%, 5%, and 1%, respectively.

A.2 Timeline of the Empirical Model

In the empirical model, a borrower's belief on HARP and the put-back policy changes with different phases of the program. We identify four phases with different beliefs and solve the dynamic refinancing problem corresponding to each belief. We then keep the implied refinancing decision within each corresponding phase. Details on the four phases are as follows:

1. From the year of mortgage origination, Y_0, to 2008, a borrower's refinancing decisions are derived under the belief that HARP does not exist and the put-back policy remains

the same. The borrower's belief on HARP will go through a series changes after the launch of HARP and its subsequent modifications in the next four years, but the borrower's belief on put-back policy will stay the same until the beginning of 2013.

2. From 2009 to 2011, HARP becomes available (HARP 1.0). HARP 1.0 is characterized by the fixed cost $\phi_{it}^{H} = \phi_0$, awareness parameter ξ_1, and an LTV ceiling of 125%. During this period, we assume that a borrower's refinancing decisions are made under the belief that HARP ends at the end of 2012.

3. In 2012, a modified version of HARP becomes available, also known as HARP 2.0, featuring the fixed cost $\phi_{it}^{H} = 0$, the awareness parameter ξ_2 and a removal of LTV cap. We obtain a borrower's refinancing decision in 2012 under the belief that HARP 2.0 ends at the end of 2013.

4. Since the beginning of 2013, the put-back policy is changed, and the end date of HARP is postponed to the end of 2018. Under this belief, we calculate a borrower's refinance decisions from 2013 to the end of the refinancing window. The post-change put-back policy eliminates the difference in expected put-back costs faced by the incumbent and the competing lenders, and lowers the expected put-back costs in general.

A.3 Model Identification

We start with supply-side parameters. First, notice that the incumbents' market share among HARP borrowers is the sum of two components: the share of non-searchers and the share of searchers multiplied by the incumbent's winning probability in the competition stage, p_0^W. Thus the level of p_0^W is implied from the observed fraction of searchers and the incumbents' market share. From equation (8), p_0^W is determined by Δ/σ_ω given the observable J. In the post-2013 period, $\Delta = \Delta_F$. Therefore, we can pin down Δ_F/σ_ω using the post-2013 market share of the incumbent and the fraction of searchers. Intuitively, Δ_F/σ_ω measures the post-2013 cost advantage of the incumbent lender relative to the dispersion of idiosyncratic cost shocks, and a larger advantage grants the incumbent higher market share in the competition stage.

The price of HARP refinancing from competing lenders experiences a change after 2013 because of the general reduction of put-back probability. The extent of the price change, together with the price level post-2013, helps determine the supply-side parameters. To see this, we calculate the difference between the mean HARP price offered by competing lenders post-2013 and the corresponding pre-2013 price (by Equations (9) and (10)):

$$E[r \mid j^* \neq 0, \text{post}] - E[r \mid j^* \neq 0, \text{pre}] = -\frac{\sigma_\omega}{M} \log\left(\frac{J + \exp(\Delta_F/\sigma_\omega)}{J\exp(-\Delta_P/\sigma_\omega) + \exp(\Delta_F/\sigma_\omega)} \right) + \frac{P_{0|post} - P_{0|pre}}{M} \tag{33}$$

where $P_{0|post} = P_{cost} \cdot p^{PB}(x, t; j = 0, Post = 1)$ and $P_{0|pre} = P_{cost} \cdot p^{PB}(x, t; j = 0, Post = 0)$ are the expected put-back costs for the incumbent post-2013 and pre-2013, respectively. Note that $\Delta_P = P_{cost} \cdot \left[p^{PB}(x, t; j \neq 0, Post = 0) - p^{PB}(x, t; j = 0, Post = 0)\right]$, and thus the only unknown part in $P_{0|post}$, $P_{0|pre}$, and Δ_P is P_{cost}. Therefore, given Δ_F/σ_ω, this price change is determined by two parameters: σ_ω and P_{cost}. The two parameters have opposing effects on the equation: P_{cost} drives up the price change while σ_ω mitigates it. In terms of magnitude, we expect P_{cost} to have a more pronounced effect on the pre-post price change, while the influence of σ_ω is more nuanced, given that it is divided by the multiplier, M. The two parameters also jointly determine the competing lender's average HARP price post-2013:

$$E[r \mid j^* \neq 0, \text{post}] = -\frac{\sigma_\omega}{M} \left[\log(J\exp(-\Delta_F/\sigma_\omega) + 1) + \frac{J\log\left(1 - (1 - p_0^W)/J\right)}{1 - p_0^W} \right] + \frac{P_{0|post}}{M} + g + c \tag{34}$$

Thus, P_{cost} and σ_ω are simultaneously determined by Equations (33) and (34), and therefore, Δ_F.

Parameters in the search cost distribution, $\bar{\kappa}$ and e, are then determined through the incumbent's prices and the fraction of searchers. Let j^o denote the observed lender, with $j^o = 0$ indicating a refinancing with the incumbent. The expected price for HARP refinancing with the incumbent lender is a linear combination of the initial quote and the conditional expectation of competitive offer, weighted by the search probability:

$$E[r \mid j^o = 0] = \Pr(S = 0)r^I + \Pr(S = 1)E[r \mid j^* = 0], \tag{35}$$

where the expected competitive offer $E[r \mid j^* = 0]$ is pinned down by supply-side parameters. As mentioned in Section 4.3.2, $\bar{\kappa}$ and e govern both the initial quote r^I and search probability. Therefore, the system of the two equations determining $E[r \mid j^o = 0]$ and $P(S = 1)$ (Equations (35) and (16)) pins down the two unknown parameters ($\bar{\kappa}$ and e).

The parameter of the relative refinancing cost, ϕ_0, governs the increase in refinance activity in response to HARP 2.0. The fixed cost of HARP 1.0 is ϕ_0, but it reduces to zero during HARP 2.0, which induces more refinancing activity in the era of HARP 2.0. The magnitude of such increase helps to identify ϕ_0. On the other hand, the unobserved utility effect of refinancing, μ, is constant over time, which can be pinned down by the overall rate of refinancing. For example, μ tends to be positive if the predicted refinancing rate based on the calculated monetary value functions is lower than the observed level, suggesting the presence of unobserved utility gain from refinancing.

The scale parameter of utility shocks to refinancing cost, σ_V, is identified by the cross-sectional variation in refinancing decisions across different markets. σ_V controls the sensitivity of refinancing decisions with respect to the value of refinancing relative to the value of waiting, which is lower if the current LTV is high but it is expected to decline as house prices in the market gradually recover from the crisis. During 2009–2011, the recovery of house prices took different trajectories in different states. If σ_V is small, the timing of refinancing decisions would exhibit significant variation across different states. Specifically, states with a faster recovery of house prices would have more refinancing activities later in that period, compared to states with a slower recovery path. Conversely, if σ_V is high, refinancing decisions are not sensitive to the calculations of future LTV changes, and there would be less variation in terms of refinancing decisions across different states. This suggests that σ_V plays a crucial role in the heterogeneity of refinancing decisions across states.

Finally, under the assumption that the decision of refinancing type is made after the refinancing decision, the relative share of HARP refinancing compared to regular refinancing during HARP 1.0 and HARP 2.0 identifies ξ_1 and ξ_2, respectively.

A.4 Idiosyncratic Housing Shock

In the first stage, we estimate the binary decision to take HARP refinancing using a probit model. This stage contains borrower and loan characteristics (FICO, income, interest rate, principal, LTV, whether first-time buyer, insurance coverage, occupancy type, number of borrowers) that affect their refinance decision but should not affect the house value (exclusion restriction). Only for those who choose to take HARP refinancing in the first stage do we observe their new home value at the time of refinance, and thus Δh_{it}. The main regression in equation (24) is estimated in the second stage. Table 12 shows the regression results from both stages.

A.5 The Effect of HARP 2.0

In this section, we evaluate the effectiveness of HARP and the subsequent modifications to HARP (HARP 2.0). Table 13 presents a summary of the key outcome variables in a series of counterfactual scenarios. In column (1), only HARP 1.0 is available throughout the 2009–2018 period. In columns (2)–(4), HARP 1.0 is implemented during the initial phase (2009–2011) followed by only one modification to a certain aspect of the program. Column (2) shows the case where the modification targets only the fixed cost of refinancing by setting $\phi^H = 0$, while other aspects remain the same as HARP 1.0. Column (3) corresponds to the case where only the program awareness is changed. In column (4) the only modification is eliminating the LTV cap requirement. Lastly, column (5) is the baseline case where HARP 2.0 encompasses all three measures.

Table 12: Idiosyncratic Housing Shock

	(1)	(2)
	First Stage HARP Refinance	Second Stage House Value
log(FICO)	0.419***	
	(0.020)	
Prev. Rate	0.007	
	(0.005)	
log(Income)	−0.082***	
	(0.004)	
log(Balance)	0.275***	
	(0.005)	
LTV	0.046***	
	(0.000)	
log(ΔHV_t)	−4.313***	1.108***
	(0.012)	(0.004)
ρ	-0.634	
σ^2	0.189	
Observations	2,146,151	208.075

This table reports the results from a Heckman two-step selection model. The first stage is a probit regression where the the dependent variable is whether a household refinanced under HARP. The second stage estimates the main regression as in equation (24). The figures in parentheses are standard errors, with 1, 2, and 3 asterisks indicating statistical significance at 10%, 5%, and 1%, respectively.

Table 13: Mean of Outcome Variables from Counterfactual and Baseline Models

	Counterfactual				Baseline
	HARP 1.0	HARP 1.0 + partial HARP 2.0			HARP 1.0+ HARP 2.0
		ϕ^H	ξ	LTV cap	
	(1)	(2)	(3)	(4)	(5)
Overall refinancing rate (%)	86.1	86.2	86.1	86.1	86.3
HARP refinancing rate (%)	3.9	4.0	5.7	4.0	6.4
Default rate (%)	8.0	8.0	8.0	8.0	7.9
Total payments	203.2	203.1	203.2	203.2	203.1
Borrower welfare	509.9	510.3	509.9	509.9	511.1
GSE profits	105.4	105.5	105.4	105.4	105.6
Investor profits	168.7	168.6	168.7	168.7	168.4

This table summarizes the average outcome variables from counterfactual scenarios (columns (1)–(4)) and the baseline model (column (5)). Column (1) corresponds to the case with only HARP 1.0 throughout 2009 to 2018, respectively. Columns (2)–(4) show the scenario where HARP 1.0 is implemented through 2009 to 2011, followed by changes in the fixed cost (ϕ^H), awareness (ξ), and LTV cap, respectively. Column (5) shows the baseline model with HARP 1.0 during 2009–2011 and HARP 2.0 afterwards, with changes in all three above-mentioned variables. Definitions of the variables are the same as in Table 6. $N = 2124700$.

In terms of extensive margin, HARP 2.0 leads to a 0.2 percentage point increase in the overall refinancing rate, with the change in fixed cost contributing the most to the increase in the overall refinancing rate. The HARP refinancing rate is 3.9% without the HARP 2.0 modifications. Given the baseline HARP refinancing rate of 6.4%, HARP 2.0 raises the utilization of the program by 64% (6.401-3.904)/3.904), with the awareness of HARP as the main contributor.

In the absence of HARP 2.0, the average 10-year default rate is 0.1 percentage point higher and total mortgage payments increase only marginally. Overall, HARP 2.0 boosts the average borrower welfare by $1,200. The reduction of fixed costs plays the most prominent role among the three factors, accounting for 40% of the effect.

The average profits for GSEs decrease slightly without the implementation of HARP 2.0 due to the weakened refinancing activities. However, investors have higher average profits in the absence of HARP 2.0, since refinancing activities generally hurt investor profits.

Overall, the welfare effect of HARP 2.0 is positive but smaller than that of the symmetric put-back risk. Note that the welfare impact of HARP 2.0 modifications comes from other channels rather than interest savings, namely reduced fixed costs, higher refinancing rates, and lower default rates. By comparison, the welfare implications of the cost asymmetry is mostly from the intensive margin of greater interest savings and earlier refinance timing.