The Discouraged Refinancer: Perceived Credit Access and Mortgage Refinancing*

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Abstract

Many mortgage borrowers do not refinance despite the potential for substantial savings. Using the New York Fed's Survey of Consumer Expectations, we assess the role of approval concerns by comparing borrowers' stated probabilities of applying to refinance under current conditions and under guaranteed approval. We combine these responses with confidential HMDA to construct borrower-specific benchmarks for refinancing rates and approval probabilities. First, we document a sizable discouragement wedge between the two probabilities: guaranteed approval nearly doubles the average probability of applying. Second, application probabilities respond about 40 percent less to better refinancing terms under current conditions than under guaranteed approval. This difference is largest among borrowers who believe they cannot qualify for refinance. Third, the discouragement wedge is larger among borrowers whose approval beliefs are more pessimistic than the HMDA-based benchmark, but it persists even among borrowers whose beliefs are close to the benchmark. These findings suggest that previous research using refinance application records may overlook selection on approval concerns. These concerns also weaken the transmission of lower rates to households. Releasing this hidden refinancing demand may require both better information about approval prospects and improved access to credit.

Keywords: mortgage refinancing, subjective expectations, credit access, discouraged borrowers, monetary-policy pass-through

JEL classification: D84, E52, G21, G51

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1 Introduction

In the United States, where most mortgages carry a fixed rate, refinancing is the main way lower interest rates reach existing borrowers and an important channel through which monetary policy affects household spending (Beraja et al., 2019; Amromin et al., 2020; Berger et al., 2021). Yet many borrowers do not refinance even when it appears financially attractive, or they refinance at the wrong time (Keys et al., 2016; Agarwal et al., 2016). Understanding why borrowers leave these gains unrealized matters for both household welfare and monetary policy transmission.

Fixed costs of applying offer a natural explanation for refinancing inaction: borrowers refinance only when the gains are large enough to justify the costs of doing so. Accounting for observed behavior, however, often requires substantial nonpecuniary costs that vary across households and over time (Campbell and Ramadorai, 2026). One reason these costs may appear large is that the gains from applying are uncertain. Refinancing offers savings only if a lender approves the new loan, while borrowers incur time, effort, and some monetary costs even if the application is rejected. A borrower may therefore recognize substantial potential savings and still be unwilling to risk an unsuccessful application. Approval concerns can thus make borrowers behave as if application costs were higher, even when the costs themselves are unchanged.

Although this mechanism is intuitive, measuring its importance is challenging. First, households act on their own approval beliefs, which we cannot recover directly from realized approval outcomes. Second, application records contain only those who chose to apply, leaving the potential demand of borrowers who expect rejection unobserved. Third, it is difficult to observe how the same borrower would respond under different approval conditions. Lenders do not randomly guarantee approval, and information experiments can shift approval beliefs, but credible personalized information requires borrower-level underwriting data and does not remove the risk of denial.

In this paper, we introduce novel survey data to study how perceived approval risk shapes refinancing demand and its relationship to interest-rate incentives. We exploit paired questions in the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE) that elicit borrowers' application probability under current conditions and under guaranteed approval. Mortgage holders report the percent chance that they will apply to refinance over the next twelve months, then report that chance under a hypothetical guarantee that any credit application they make will be approved. The hypothetical makes approval certain while keeping the borrower, mortgage, and horizon of the questions unchanged. We call the difference between the two answers the *discouragement wedge* and refer to a positive wedge as *hidden demand*: the additional probability of applying that a borrower reports when approval is guaranteed. The wedge captures demand held back by perceived approval risk, whether or not borrowers assess that risk accurately.

We combine the survey with confidential Home Mortgage Disclosure Act data (cHMDA). Using models estimated on cHMDA refinance applications, we predict, for each respondent, the refinancing rate she could obtain and her probability of approval, based on characteristics observed in both data sets. The difference between the respondent's current rate and her predicted rate measures the potential gain from refinancing. We use the predicted approval probability to identify borrowers with strong observable approval prospects and to compare respondents' subjective approval beliefs with an objective benchmark.

Our analysis covers 8,988 respondent-wave observations from 2017 to 2025, spanning the refinancing boom and the subsequent rise in mortgage rates. The survey has three advantages for studying approval concerns. First, it covers all mortgage holders, including those who do not intend to apply, so it observes borrowers who are absent from application records because they expect rejection. Second, it separately elicits three measures of perceived access, which allow us to test whether hidden demand reflects approval concerns: expected rejection as a reason for not applying, the subjective probability of approval, and the mortgage rate respondents believe they could obtain. The rate question allows the answer "would not qualify at any rate," which distinguishes beliefs about the availability of credit from beliefs about its price. Third, repeated interviews allow us to validate stated probabilities of applying against subsequent applications. Assuming applications are spread evenly over the year, a 10 percentage point higher stated probability of applying over the next twelve months translates into an approximately 4 percentage point higher probability of applying within the year, so stated probabilities carry substantial information about behavior.[1]

Our first finding is that hidden demand is substantial. Under guaranteed approval, the average stated probability of applying nearly doubles, from 7.6 to 13.8 percent. This increase is concentrated among the almost one in five borrowers with a positive wedge, whose average probability of applying rises from 17 to 55 percent under the guarantee. The three measures of perceived access previously introduced confirm that this hidden demand reflects approval concerns: the discouragement wedge is particularly large among borrowers who say they expect to be rejected, who report a low chance of approval, or who say they would not qualify at any rate, and it is close to zero among borrowers who are certain of approval.

Hidden demand is also economically relevant. It varies over the refinancing cycle but remains substantial throughout: current and guaranteed application probabilities both move with the cycle, and the gap between them persists. Hidden demand also varies with refinancing incentives and is largest where the gains from refinancing are largest. Comparing borrowers surveyed in the same month, the wedge averages about 4 percentage points among borrowers whose rate is below the

[1] We observe applications over the four months following each interview, during which a 10 percentage point higher stated probability is associated with a 1.3 percentage point higher probability of applying. We scale this estimate by three to match the twelve-month horizon. Section 3.2 describes the exercise and alternative timing assumptions.

predicted rate available to them, and it is about 9 points larger among those whose rate exceeds it by more than 100 basis points.

Turning to the predictors of discouragement, it is more common among borrowers with weaker credit profiles, as expected if it reflects approval concerns, and among borrowers with higher mortgage rates and larger balances, who have more to gain from refinancing. It is not confined to borrowers with weak credit, however: among borrowers with strong observable approval prospects, the wedge rises with potential savings by a similar amount. Approval concerns therefore hold back refinancing demand where a new loan would be most valuable, including among borrowers who are likely to be approved.

We then develop a simple application model to understand what these patterns imply for refinancing responses. Applying is worthwhile when the value of a successful refinance, weighted by the perceived probability of approval, exceeds the application cost. Approval risk raises the hurdle that refinancing gains must clear. Better rates can therefore make applying worthwhile under guaranteed approval while leaving it unattractive under current conditions. The framework motivates two tests: whether refinancing intentions respond more strongly to incentives under guaranteed approval, and whether the difference is greater among borrowers who perceive more limited access.

The first comparison reveals substantial *lost pass-through*: approval concerns weaken the response of refinancing demand to better terms. A one percentage point increase in the average gap between borrowers' existing mortgage rates and their predicted refinancing rates raises the probability of applying under guaranteed approval by 2.4 percentage points, but the probability under current conditions by only 1.5 points. About 40 percent of the response under guaranteed approval is therefore missing from current application probabilities. This lost pass-through is not limited to borrowers with weak credit: more than a third of the response is still missing among borrowers whose observable characteristics predict a high chance of approval.[2]

The second comparison shows that the lost response is concentrated among borrowers who doubt their access to credit, a pattern that holds across all three separately elicited measures of perceived access. First, among respondents certain of approval, current and guaranteed probabilities respond similarly to the rate gap, and the wedge does not respond significantly. As doubt about approval rises, the wedge responds more strongly: at the lower quartile of approval beliefs, about 35 percent of the response under guaranteed approval is missing under current conditions. Second, among low-intention respondents who cite expected rejection as a reason for not applying, the response under guaranteed approval is more than 20 times that of respondents who give other

[2]The average rate gap also reflects aggregate conditions and sample composition, so these estimates describe conditional associations with the refinancing environment. Specifications using borrower-specific rate gaps and time fixed effects yield the same ordering of current and guaranteed responses.

reasons. Third, among respondents who believe they would not qualify at any rate, the response under guaranteed approval is more than three times that of respondents whose perceived qualifying rate is close to the benchmark, while their response under current conditions is similar. By contrast, respondents who expect to pay above-benchmark rates show no additional lost pass-through. These patterns distinguish doubts about obtaining credit from pessimism about its price: favorable rates can increase the value of refinancing without overcoming concerns about access.

Finally, comparing approval beliefs with the cHMDA benchmark shows that hidden demand reflects both approval risk and pessimism. Among borrowers with strong observable approval prospects, those whose beliefs are within five percentage points of the benchmark still hold back about a quarter of the demand they report under guaranteed approval. The share rises to about a third for beliefs 5–15 points below the benchmark and to more than 60 percent for beliefs more than 50 points below it. Borrowers with below-benchmark beliefs make up about a third of this sample but account for about two thirds of the aggregate wedge. Pessimism therefore amplifies discouragement, but substantial discouragement remains even when beliefs are close to the benchmark.

Taken together, these findings show why measuring hidden demand matters beyond identifying pessimistic approval beliefs. Even borrowers who assess their prospects accurately may forgo applying because they incur application costs before knowing whether they qualify. Measuring the discouragement wedge reveals a margin of credit access that application records alone cannot capture and helps explain why refinancing demand may respond weakly to lower rates. Reducing approval risk or application costs may therefore complement better information about approval prospects in helping borrowers benefit from lower rates.

Literature Review. Our paper first relates to the literature on refinancing inaction. A large literature documents that households fail to refinance when it would be optimal to do so (Campbell, 2006; Agarwal et al., 2016; Keys et al., 2016; Bajo and Barbi, 2018; Johnson et al., 2019). Models with fixed costs imply that borrowers should refinance once the rate gap exceeds a threshold that reflects fees and the option value of waiting (Agarwal et al., 2013), but observed inaction exceeds what this threshold implies (Keys et al., 2016). Structural models therefore add nonpecuniary costs of acting, such as psychological costs and intermittent attention (Andersen et al., 2020), and estimate that these costs are high and vary across households (Fisher et al., 2024; Belgibayeva et al., 2026). What these estimated costs represent remains an open question (Campbell and Ramadorai, 2026). A closely related paper is Agarwal et al. (2024), who show that approval risk shapes how borrowers search across lenders and makes riskier borrowers behave as if they had higher search costs. We study the earlier decision of whether to apply, measure approval beliefs directly, and elicit the additional demand borrowers would express under certain approval. This perspective helps interpret refinancing inaction: approval risk can raise the gain needed to justify applying even

when beliefs are accurate, and pessimism can raise this hurdle further.

The role of these beliefs connects our paper to research on household expectations. Survey evidence links household beliefs to portfolio choices (Giglio et al., 2021) and housing and mortgage decisions (Armona et al., 2019; Bailey et al., 2019). Survey questions on discouraged borrowers identify households that did not apply for credit because they expected to be turned down (Jappelli, 1990), but beliefs about whether a lender would approve an application have received comparatively little attention, despite their role in determining whether households seek credit at all. Existing evidence shows that many households overestimate the credit score and down payment needed to qualify for a mortgage (Huang et al., 2017), and that making credit reports freely available increased mortgage applications and approvals (Kumar, 2021). Approval beliefs may reflect limited information about lending standards or personal experiences, consistent with broader evidence that experience shapes expectations (Malmendier and Nagel, 2011; Kuchler and Zafar, 2019; Cenzon, 2026). We contribute by connecting directly elicited approval beliefs and other measures of perceived access to hidden refinancing demand, and by comparing these beliefs with an approval benchmark based on observably similar applicants.

Our paper also contributes to research on refinancing and monetary policy transmission (Beraja et al., 2019; Di Maggio et al., 2020; Berger et al., 2021; Eichenbaum et al., 2022). Studies of refinancing constraints show how documentation requirements, loan-to-value limits, and borrower credit characteristics restrict households' ability to benefit from lower rates (DeFusco and Mondragon, 2020; Agarwal et al., 2023; Gerardi et al., 2023). We complement this evidence by examining how perceived approval barriers relate to the response of refinancing intentions to interest-rate incentives, including among borrowers with strong observable approval prospects.

Our measurement approach builds on research using hypothetical survey questions to elicit responses to changes that are difficult to observe or implement. Applications include changes in income (Jappelli and Pistaferri, 2014; Fuster et al., 2021), financing conditions (Fuster and Zafar, 2021), pension eligibility ages (Caplin et al., 2022), and job characteristics or location (Wiswall and Zafar, 2018; Koşar et al., 2022). Such questions complement randomized information experiments and can be administered in a single survey wave to the full sample (Coibion and Gorodnichenko, 2026). Evidence comparing reported responses with observed behavior supports the usefulness of these methods (Parker and Souleles, 2019; Colarieti et al., 2024). We apply this approach to credit-market participation by eliciting application probabilities under current conditions and guaranteed approval from the same borrowers, including those who do not currently plan to apply.

2 Data and Measurement

The paper combines two data sources: the Survey of Consumer Expectations (SCE) and the confidential Home Mortgage Disclosure Act data (cHMDA). This section describes each data source in turn and concludes with our final sample and summary statistics.

2.1 Survey of Consumer Expectations (SCE)

One of our main data sources is the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). The SCE is an internet-based rotating panel of U.S. household heads that combines detailed demographic information with probabilistic expectations about future economic outcomes. We combine two of its special modules: the Credit Access module, which records households' credit-market behavior and their beliefs about access to credit, and the Housing module, which describes their home and mortgage contract.

The Credit Access module is administered every four months, and respondents typically participate up to three times. The module records respondents' existing debt, recent credit applications and their outcomes, intended future borrowing, subjective approval beliefs, and self-reported credit-score ranges. A particularly useful feature is its probabilistic elicitation of future credit demand. Respondents report the percent chance that they will undertake several credit-market actions over the next twelve months, including applying to refinance an existing mortgage. Beginning in 2016, the survey asks them to report these probabilities again under a hypothetical scenario in which any credit application is guaranteed approval. For mortgage refinancing, the two questions read:

> **Refinance application probability.** *Over the next 12 months, what do you think is the percent chance that you will do any of the following?*
>
> *Request to refinance your mortgage:* _____%

> **Guaranteed-approval refinance application probability.** *Now consider the hypothetical scenario where you are guaranteed that any credit application you may make over the next 12 months will be accepted for sure. If you knew that your application would be approved for sure, what do you think is the percent chance that you will do any of the following over the next 12 months?*
>
> *Request to refinance your mortgage:* _____%

These questions allow us to construct our key measure of discouragement, defined in Section 3.1.

The Housing module is administered annually, so we have one observation per respondent. It provides detailed information on the household's home and mortgage contract, including the purchase price, current and expected home value, original and outstanding mortgage balances, monthly mortgage payments, and the interest rate on the existing mortgage.

Moreover, both Housing and Credit modules provide three measures of perceived credit access used throughout the paper:

Reasons for not applying. Respondents who report a probability of applying below 10 percent are asked why they are unlikely to apply. They are offered possible reasons such as high rates, cost or effort, and expectation of rejection. Those who choose expected rejection are then asked which credit products they might need or want but will not apply for in the next 12 months because they think they would not be approved. If they select "Refinance mortgage", we interpret rejection concern as a perceived constraint on access to refinancing.

Refinance approval probability. Respondents who report an application probability equal to or above 5 percent are asked their probability that a refinancing application would be approved conditional on applying:

> *If you were to apply for a mortgage refinance over the next 12 months, what do you think is the percent chance that your request would be granted?*

This provides us with a direct measure of subjective approval probabilities.

Potential mortgage rate. Lastly, SCE asks about their potential mortgage rate if they were to apply for a mortgage today. This is asked from all participants without sample restrictions and independently of their stated probability of applying.

> *Assume that you applied for a 30-year fixed-rate mortgage today. What mortgage interest rate do you think you would qualify for?*
> *Mortgage Rate:* _____ %
> □ *Would not qualify at any rate*

Respondents can either report the potential mortgage rate or indicate that they would not qualify at any rate. We interpret the response "not qualify at any rate" as a perceived constraint on mortgage access rather than the price they could obtain.

These three measures of perceived credit access can be linked to each respondent probability of applying. Together, the two modules allow us to estimate the potential economic gains from refinancing while also observing borrowers' intent to refinance and their perceptions of their ability to access this credit.

2.2 Home Mortgage Disclosure Act Data (cHMDA)

Our second data source is confidential Home Mortgage Disclosure Act (cHMDA) data. HMDA covers most mortgage applications in the United States and records application outcomes alongside detailed borrower, loan, and property characteristics. The confidential data provide additional detail on credit scores, property values, and application timing that helps predict mortgage pricing and approval. We use these data to construct two borrower-specific benchmarks that the survey alone cannot provide: the refinancing rate available to an observably similar borrower and the approval probability of an observably similar applicant.

Both benchmarks come from prediction models estimated on conventional, owner-occupied, first-lien, 30-year refinance applications. The models use only characteristics observed in both data sets: credit score, loan-to-value (LTV), loan amount, income, debt-to-income (DTI), property value, age, gender, race, state, and the month of application. We estimate them with gradient-boosted trees, which allow for the nonlinearities and interactions that characterize mortgage pricing and underwriting, such as the joint treatment of credit score and LTV, and apply the fitted models to each SCE respondent. Appendix B describes the samples, the harmonization of variables across the two data sets, and the models.

Refinancing rate benchmark. Rather than predicting the refinancing rate directly, we predict its spread over the Average Prime Offer Rate (APOR). The spread captures how lenders price a borrower's characteristics; adding the APOR in the month of the interview places that price in the rate environment the respondent faces. Her predicted refinancing rate and rate gap are

$$\widehat{r}_{it} = \widehat{\text{Spread}}_i + \text{APOR}_t, \qquad \Delta r_{it} = r_{it}^{\text{current}} - \widehat{r}_{it} \tag{1}$$

where r_{it}^{current} is the rate she reports on her existing mortgage. A larger Δr_{it} means a larger potential rate gain from refinancing. The measure is conservative in two respects. The benchmark is a 30-year loan, although some borrowers could obtain a lower rate on a shorter term. It is also the annual percentage rate (APR), which includes points and lender fees, whereas the survey asks for the interest rate on the existing mortgage. A positive rate gap therefore means that the borrower's current rate exceeds the rate on a new 30-year loan plus the points and fees needed to obtain it.[3]

Approval probability benchmark. The approval model predicts whether a refinance application is approved, counting applications that were originated or approved but not accepted as approved

[3]The APR includes the interest rate, discount points, lender fees, and mortgage insurance, but not third-party closing costs such as appraisal and title fees. The benchmark is therefore conservative relative to a comparison of interest rates, without being a complete accounting of the cost of refinancing.

and denied applications as not approved. Applied to a respondent, it gives

$$\widehat{q}_i = \Pr(\text{approved} \mid X_i), \tag{2}$$

the approval rate of applicants with observable characteristics X_i. While $\widehat{q}_i$ is a reasonable benchmark for a respondents' approval prospects, it is not the true approval probability: it omits information that lenders see but cHMDA does not record, and it is estimated among borrowers who chose to apply. Section 6.1 discusses how we interpret it.

Both models predict well out of sample. On a 20 percent hold-out sample of cHMDA applications, the rate model has an R^2 of 0.45 and the approval model an AUC of 0.89: given a randomly chosen approved applicant and a randomly chosen denied applicant, the model assigns the higher approval probability to the approved one 89 percent of the time. The characteristics that drive the predictions also match how mortgages are priced and underwritten (Appendix B.4). The approval benchmark also predicts the outcomes of SCE respondents whom we later observe applying. Across the top four fifths of predicted approval, predicted approval averages 92 percent and realized acceptance 91 percent. In the bottom fifth, the model understates acceptance (Appendix B.5).

2.3 Analysis sample and summary statistics

The analysis uses a single sample of mortgage holders with observed application probabilities under current conditions and guaranteed approval, together with the characteristics needed to construct the borrower-specific refinancing rate gap. The sample contains 8,988 respondent-wave observations over 2017–2025. Forty-five percent of respondents contribute three waves, accounting for 60 percent of observations (Appendix Table A2).

The availability of perceived-access measures varies with survey routing. Respondents are shown questions about reasons for not applying in 81.3 percent of observations and the approval-belief question in 34 percent, with 15 percent routed to both. A qualifying-rate response is recorded for 99.5 percent of observations. Appendix Table A1 reports the full breakdown.

The sample is concentrated among respondents with high education and income: 78.4 percent have a college degree, 47.3 percent report household income of at least $100,000, and 4.3 percent report income below $30,000. About half are aged 35–54 and a further third are aged 55 or older. Appendix Table A3 reports the full sociodemographic characteristics.

Borrowers generally have substantial equity and strong credit profiles. The average outstanding mortgage balance is about $182,000, against a self-assessed home value of $377,000, and the average loan-to-value ratio is 53.9 percent. The average mortgage rate is 3.9 percent and the

monthly payment is $1,488. Self-reported credit scores exceed 760 in 59.2 percent of observations and are at least 680 in 88.2 percent. Appendix Table A4 provides additional mortgage and housing characteristics.

The rate gap (Δr_{it}) averages -1.2 percentage points, meaning that borrowers' existing mortgage rates are, on average, below their predicted refinancing rates. Even so, 25 percent of respondent-waves have a positive gap, indicating potential rate savings from refinancing. This share varies substantially over time, averaging 64 percent during the 2020–2021 refinancing boom and 4.8 percent in 2023–2025 (Appendix Figure A3). Predicted approval ($\widehat{q}_{it}$) averages 81 percent, and 75 percent of observations have $\widehat{q}_{it} \geq 0.80$. We refer to this group as *observably approvable* borrowers.

3 Hidden Refinancing Demand

This section documents what the paired questions reveal before we impose any model. We show how common hidden demand is and how it is distributed, that it behaves as a measure of approval concerns should, its variation over the cycle and with incentives, and what borrowers' characteristics predict it.

3.1 Measuring hidden demand

For each respondent-wave we observe

- p_{it}^{subj}: subjective probability of applying to refinance under current conditions over next 12 months.
- p_{it}^{G}: subjective probability of applying to refinance if approval were guaranteed over next 12 months.

and define the *discouragement wedge* as

$$\Delta p_{it} \equiv p_{it}^{G} - p_{it}^{\text{subj}} \tag{3}$$

The two answers come from the same person, concern the same mortgage, and cover the same horizon. The within-borrower comparison therefore holds baseline circumstances fixed, including observed and unobserved borrower characteristics. The wedge measures the change in the stated probability of applying when approval is guaranteed. We refer to a positive wedge as *hidden demand* and to borrowers with $\Delta p_{it} > 0$ as *discouraged*.

Incidence and distribution. Averaged over all mortgage holders, guaranteed approval raises the stated probability of applying from 7.6 to 13.8 percent. The paired questions show where this increase comes from. Table 1 classifies respondent-waves by how their two answers compare. Most respondents give the same answer in both scenarios: 62.5 percent report no probability of applying in either, and 14.5 percent report a positive probability that the guarantee leaves unchanged. The increase comes from the 17.9 percent with a positive wedge, whose average probability of applying rises from 17 to 55 percent (Panel B).

Table 1: Application probabilities and the discouragement wedge

Panel A: Response patterns

Current p_{it}^{subj}	Discouragement Wedge $\Delta p_{it} = p_{it}^{G} - p_{it}^{\text{subj}}$	Interpretation	Share (%)
0	0	No stated demand in either scenario	62.5
> 0	0	Positive demand, unchanged by guaranteed approval	14.5
0	> 0	Positive demand only under guaranteed approval	5.6
> 0	> 0	Higher application probability in guaranteed approval	12.3
> 0	< 0	Reversal	5.1
		Total discouraged ($\Delta p_{it} > 0$)	**17.9**

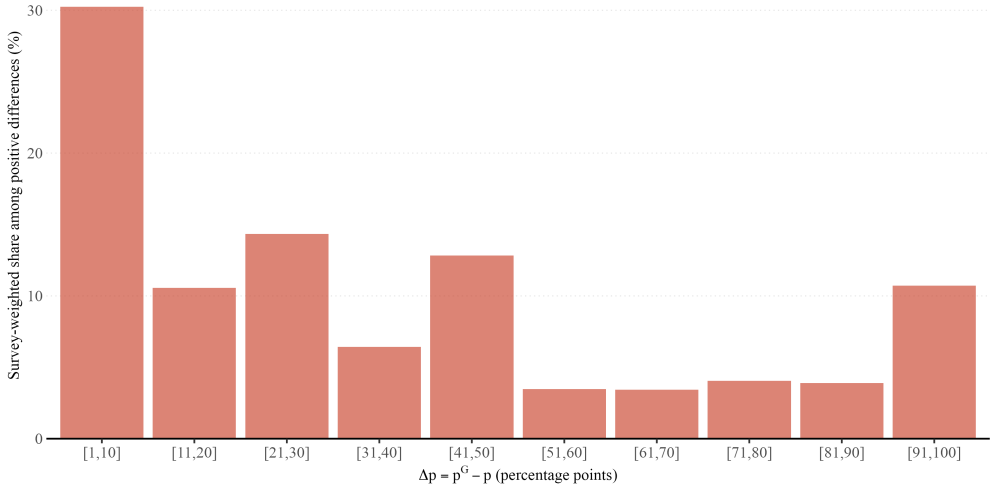
Panel B: Average application probabilities

Sample	$\bar{p}^{\,\text{subj}}$ (%)	$\bar{p}^{\,G}$ (%)	$\overline{\Delta p}$ (pp)	Relative increase (%)
All respondents	7.59	13.77	6.18	81.4
Discouraged ($\Delta p_{it} > 0$)	17.02	55.09	38.06	223.6

Notes: Survey-weighted statistics for 8,987 respondent-waves. The wedge is $\Delta p_{it} = p_{it}^{G} - p_{it}^{\text{subj}}$, where p_{it}^{subj} is the stated probability of applying to refinance over the next twelve months under current conditions and p_{it}^{G} is the probability under guaranteed approval. Appendix Figure A1 shows the distribution of both p_{it}^{G} and p_{it}^{subj}. In Panel A, the first five rows sum to 100 percent; the final row combines rows 3 and 4. In Panel B, bars denote survey-weighted means within each sample. The relative increase is $100 \times \overline{\Delta p} / \bar{p}^{\,\text{subj}}$.

Most of these discouraged borrowers report a positive probability of applying even under current conditions. The wedge therefore captures both lower application probabilities among borrowers who might still apply and demand that appears only under guaranteed approval. Figure 1 shows that the wedge is large for many discouraged borrowers: about 70 percent report an increase above 10 percentage points, and about one in nine report an increase above 90 points.

Figure 1: Distribution of the discouragement wedge among respondents with $\Delta p_{it} > 0$



Notes: Survey-weighted distribution of $\Delta p_{it} = p_{it}^{G} - p_{it}^{\text{subj}}$ among respondent-waves with $\Delta p_{it} > 0$ (17.9 percent of the sample). Bars sum to 100 percent. Bins are ten percentage points wide.

The 5.1 percent who report a lower probability under the guarantee most likely reflect response error, since a guarantee cannot make applying less attractive. Most of these reversals are small, within 10 points of zero. We keep them in all analyses. Response error likely affects both questions and so also produces spurious positive wedges, and dropping only the negative ones would remove one side of this error. Appendix Figure A2 shows the full distribution of Δp_{it}.

3.2 Validation

Predictive validity: probabilities of applying predict new applications. Our analysis relies on respondents' stated probabilities of applying to refinance, so a natural concern is that these answers might carry little information about what households actually do. The panel structure of the SCE allows us to test this directly. The Credit Access module asks respondents whether they applied to refinance in the previous twelve months, and respondents are interviewed up to three times at four-month intervals. Among respondents who report no application at a given interview, any application reported at the next interview must have been submitted in the intervening four months. This allows us to compare each respondent's stated probability of applying with whether they actually applied in the four months that followed. Because the probability question refers to the next twelve months, we observe outcomes only over the first third of the forecast horizon.

We find that stated intentions strongly predict these new applications (Appendix Table D1). To compare stated and realized behavior over the same twelve-month horizon, we assume that applications are spread evenly over the year, so that the twelve-month application rate is three

times the four-month rate.[4] Under this assumption, a 10 percentage point higher stated probability corresponds to about 4 percentage point higher probability of applying within twelve months (s.e. 0.7), about two thirds of the average annual application rate of 6 percent. The estimate is essentially unchanged when we control for demographics, credit score, the mortgage rate, and the loan-to-value and debt-to-income ratios, so stated intentions contain information about behavior beyond the observable incentive and ability to refinance. The relationship is convex. Compared with respondents who report a zero probability, those reporting between 41 and 60 percent are about 15 percentage points more likely to apply within a year, and those reporting more than 60 percent about 43 percentage points more likely, while differences among low stated probabilities are small. Stated probabilities therefore predict behavior but do not translate into it one-for-one: roughly 40 percent of a difference in stated probabilities appears as a difference in applications. Appendix Table D1 reports the full results.

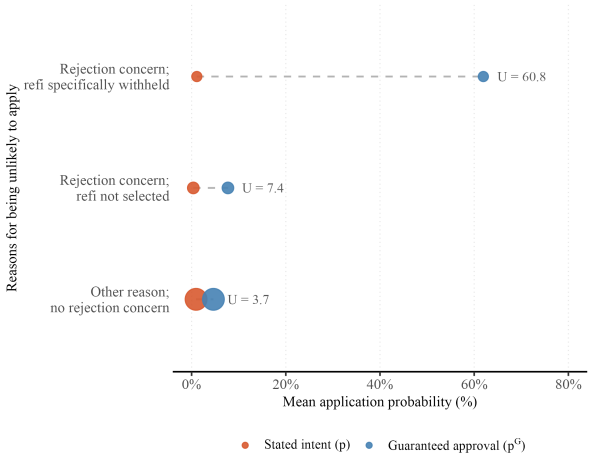
Construct validity: the wedge tracks perceived credit access. A natural concern with any hypothetical question is that respondents give more favorable answers simply because the scenario sounds more favorable, without responding specifically to its content. To assess whether the response reflects approval concerns, we relate the wedge to three measures of perceived credit access previously introduced. Figure 2 shows how the wedge behaves across these three measures.

Panel (a) focuses on respondents with low intentions, who are asked why they are unlikely to seek credit. Among those who say refinancing is something they need or want but will not pursue because they expect to be rejected, the probability of applying rises from close to zero to more than 60 percent under the guarantee, a wedge of 61 points. Among those who cite other reasons, the wedge is 4 points. Panel (b) focuses on respondents that report relatively higher intentions of applying and are then asked about their subjective beliefs about approval. The wedge falls steadily with this belief, from about 26 points among respondents who put their chances between 1 and 40 percent to 3 points among those certain of approval.Panel (c) focuses on responses about the rate at which they believe they would qualify for a new mortgage. Those who say they would not qualify at any rate report a wedge of 21 points, against 6 points for those who report a qualifying rate.

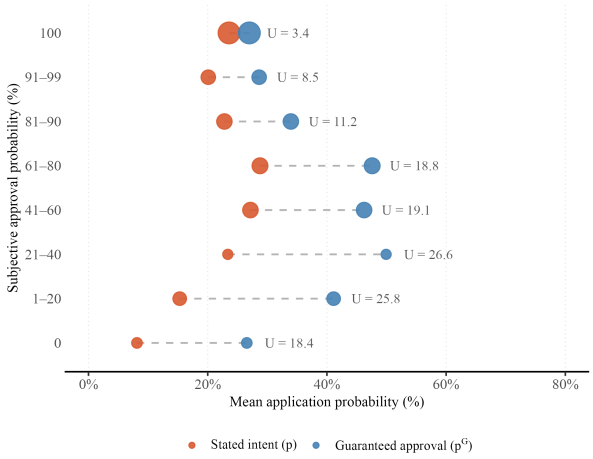
Across the three measures, guaranteed approval raises application probabilities most among borrowers who separately report concerns about qualifying. Respondents who already consider approval certain report little change, since for them the guarantee removes no barrier. These contrasts suggest that respondents react to the approval condition itself rather than simply reporting

[4] If borrowers with high stated probabilities tend to apply early in the year, this scaling overstates their twelve-month application rate; if they tend to delay, it understates it. Assuming instead that the probability of applying is the same in each four-month period gives somewhat smaller differences for respondents who report high probabilities. The table reports the four-month estimates.

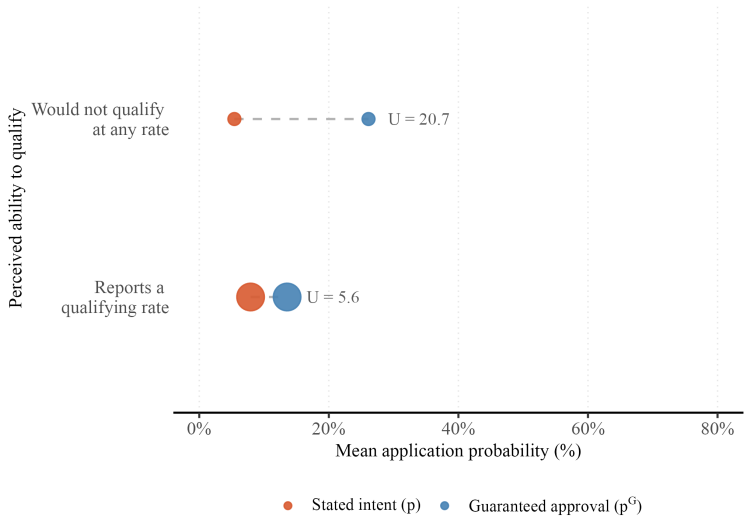
higher probabilities in a more favorable scenario.[5]



(a) Reasons for low application intent



(b) Subjective approval beliefs



(c) Perceived ability to qualify

Figure 2: Discouragement and independently elicited measures of perceived credit access

Notes: Points report weighted mean probabilities of applying under current conditions, p_i^{subj}, and under guaranteed approval, p_i^G; the distance between them is the discouragement wedge $\Delta p_i = p_i^G - p_i^{\text{subj}}$. Point size is proportional to the number of respondent-wave observations in each group. Panel (a) uses respondents routed to questions about reasons for low credit demand. The refinance-specific rejection category consists of respondents who subsequently report that refinancing is something they might need or want but would not pursue because they expect rejection; the pooled other-reason category need not refer exclusively to refinancing. Panel (b) uses the direct subjective probability that a refinance application would be approved. Panel (c) distinguishes respondents who report a numeric qualifying mortgage rate from those who state that they would not qualify at any rate.

[5]These comparisons do not establish that respondents hold every other feature fixed: guaranteed approval might also lead them to imagine easier documentation, different loan terms, or a less burdensome application process. If such features drove the response, however, we would expect respondents who are certain of approval to report higher probabilities under the guarantee as well.

3.3 Variation over the cycle and with refinancing incentives

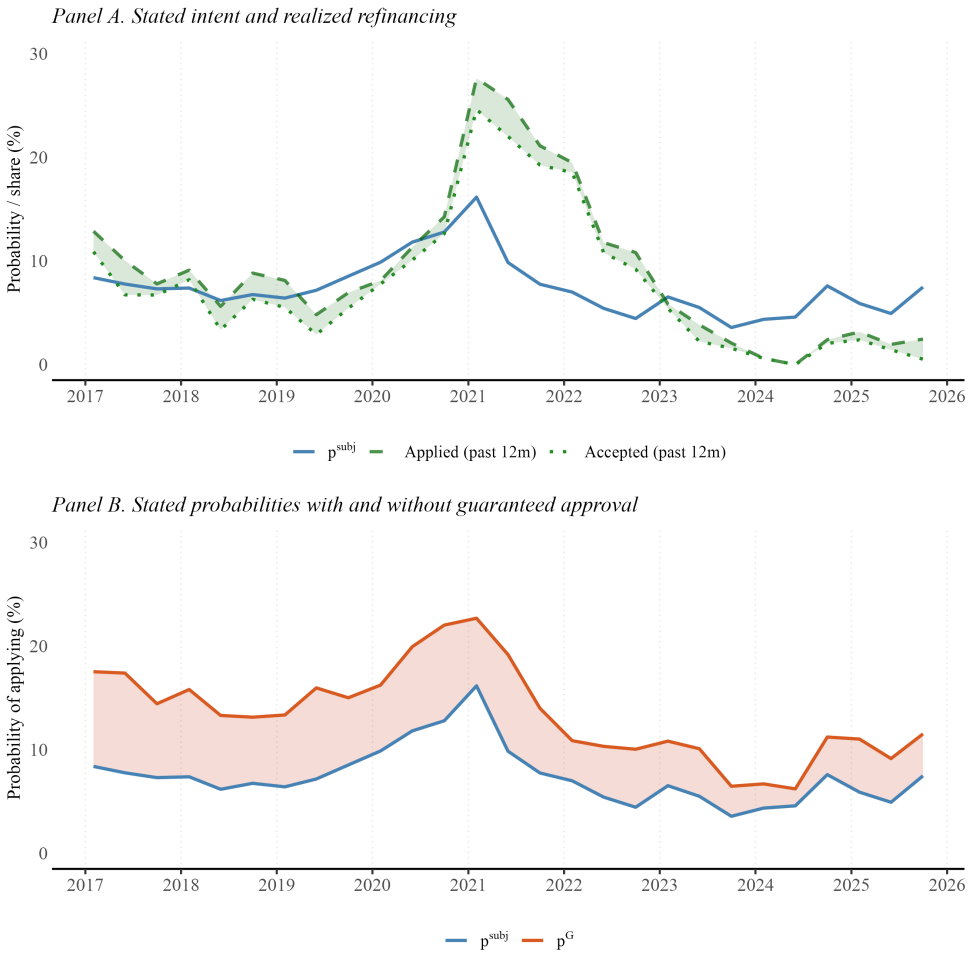
The survey period spans sharp changes in refinancing conditions: mortgage rates fell to historic lows in 2020–2021 and rose rapidly from 2022. Figure 3 Panel A compares stated demand with realized refinancing over this cycle. Both come from the SCE: respondents report the probability that they will apply to refinance over the next twelve months, and whether they applied, and were accepted, over the previous twelve months. Realized applications surge during the boom and subsequently collapse, and the share of respondents reporting an accepted refinance moves closely with applications: about 85 percent of those who report applying report an accepted application (Appendix Table A5), consistent with approval being common among those who apply. Forward-looking stated demand follows the same broad cycle, consistent with borrowers responding to refinancing incentives both in what they do and in what they say they intend to do.

Panel B shows that substantial hidden demand remains throughout this cycle. The application probability under current conditions peaks at roughly 14 percent, compared with 22 percent under guaranteed approval. The wedge averages about 7–8 percentage points both before and during the boom, reaching nearly 9 points in some waves. It falls to about 4 points in 2023–2025, when most borrowers' mortgage rates were below market rates. High acceptance among applicants therefore coexists with substantial demand held back by approval concerns, including during the boom when falling rates create particularly valuable refinancing opportunities.

To examine whether hidden demand is larger where borrowers have more to gain, we compare borrowers with different rate gaps surveyed in the same month. Figure 4 reports estimated differences in the discouragement wedge across rate-gap groups, controlling for survey-month fixed effects. The reference group consists of borrowers whose existing mortgage rate is more than 100 basis points below their predicted refinancing rate. The wedge increases steadily with the rate gap: among borrowers whose existing rate exceeds the predicted rate by more than 100 basis points, it is about 9 percentage points larger than in the reference group. The gradient is similar without month fixed effects, suggesting that it is not simply driven by common movements over the refinancing cycle. Appendix Figure D1 reports the full rate-gap distribution and a binscatter of the wedge against the gap.

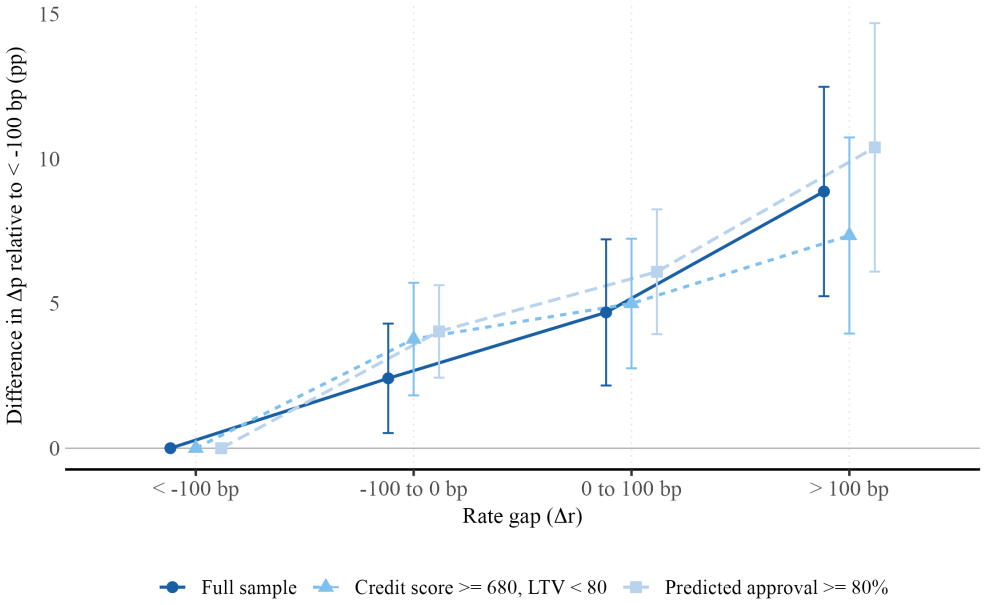
The gradient also persists among borrowers with strong observable approval prospects. Among those with predicted approval of at least 80 percent, the wedge is about 10 percentage points larger in the highest rate-gap group than in the reference group. The corresponding difference is about 7 points among borrowers with credit scores of at least 680 and loan-to-value ratios below 80 percent. The gradient also persists after controlling for credit, mortgage, and demographic characteristics (Appendix Table D3). Hidden demand thus increases with potential rate savings even among borrowers who appear likely to qualify.

Figure 3: Stated demand and realized refinancing over the refinancing cycle



Notes: Weighted monthly means from the SCE. Panel A: p_{it}^{subj} is the stated probability of applying to refinance over the next twelve months under current conditions. The dashed and dotted lines are the share of respondents who report having applied to refinance, and having had an application accepted, over the previous twelve months. The shaded band is the share who applied but were not accepted. Realized applications and acceptances are retrospective measures covering activity over the prior year, whereas stated application probabilities are forward-looking over the next twelve months. The two sets of series should therefore not be interpreted as directly comparable in levels. Panel B: the stated probability of applying under current conditions, p_{it}^{subj}, and if approval were guaranteed, p_{it}^{G}. The shaded band is the discouragement wedge, $\Delta p_{it} = p_{it}^{G} - p_{it}^{\text{subj}}$.

Figure 4: Discouragement wedge by rate gap and approval prospects



Notes: Differences in the discouragement wedge Δp_{it} across groups of the borrower-specific rate gap Δr_{it} of equation (1), relative to borrowers whose rate is more than 100 basis points below the predicted refinancing rate. Estimates come from survey-weighted regressions of Δp_{it} on rate-gap group indicators and survey-month fixed effects, estimated separately for the full sample (8,987 respondent-waves), borrowers with a credit score of at least 680 and a loan-to-value ratio below 80 percent (6,841), and borrowers with predicted approval $\widehat{q}_i \geq 0.80$ (6,737). The average wedge in the reference group is 3.9, 2.7, and 2.1 percentage points, respectively. In the full sample, the four groups contain 49, 26, 17, and 8 percent of observations. Vertical bars show 95 percent confidence intervals based on standard errors clustered by respondent. Appendix Table D3 reports estimates with borrower controls.

3.4 What predicts discouragement?

Figure 5 relates the incidence of discouragement to borrower and mortgage characteristics using a survey-weighted linear probability model for $\Delta p_{it} > 0$, controlling for all characteristics shown and wave fixed effects. Most demographic characteristics have no statistically significant association with discouragement in this specification. Appendix Table D2 reports the full results.

Discouragement is more common among borrowers with weaker credit profiles. Borrowers with credit scores below 720 are 10–13 percentage points more likely to be discouraged than those with scores above 760. Those with debt-to-income ratios of at least 50 percent are 9.5 percentage points more likely to be discouraged than those with ratios below 36 percent. Loan-to-value ratios, however, have no statistically significant association with discouragement.

Discouragement is also more common among borrowers whose mortgage characteristics suggest greater potential refinancing gains. An additional $100,000 of outstanding balance is associated with a 1.9 percentage point higher probability of discouragement, and a one percentage point higher

mortgage rate with a 2.2 percentage point higher probability. Other things equal, a higher existing rate increases potential interest savings, while a larger balance increases the dollar savings from a given rate reduction. Together, these associations support the economic relevance of the measure: discouragement is more common where observable characteristics suggest greater approval risk and where refinancing could offer larger savings.

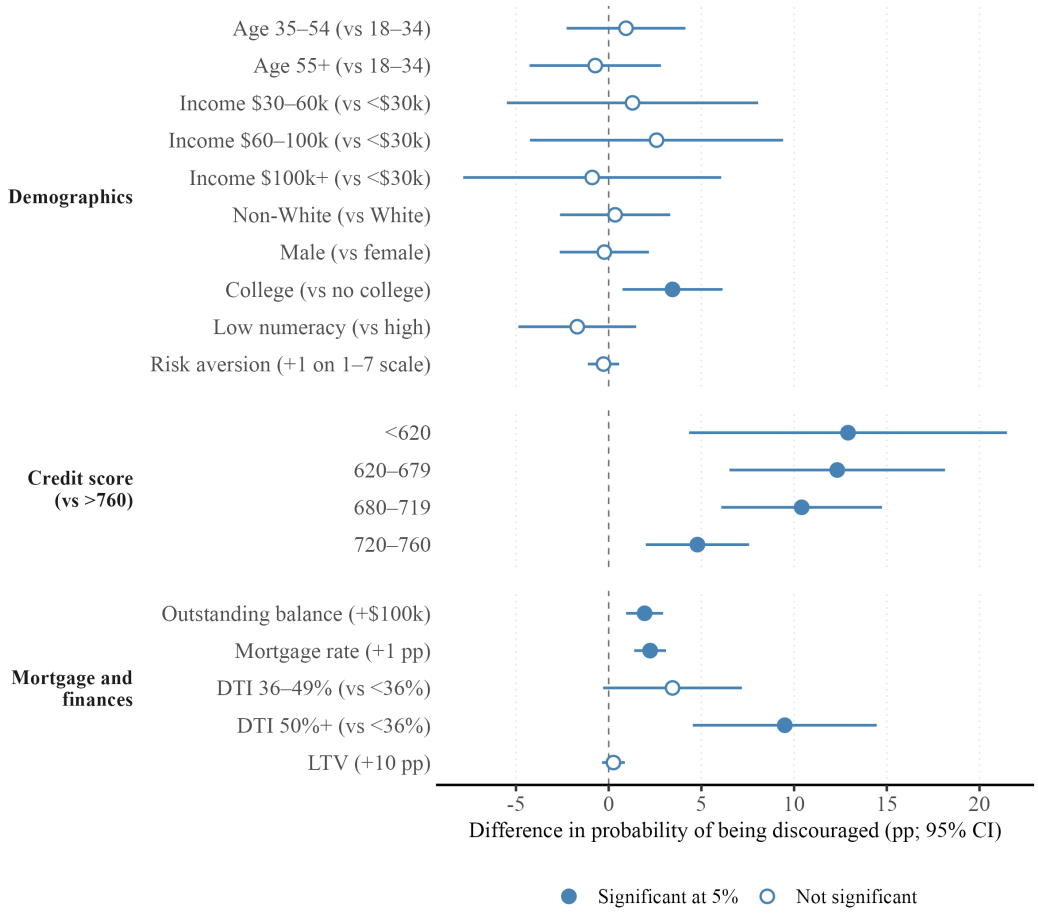


Figure 5: Who is discouraged?

Notes: The figure reports conditional differences in the probability of being discouraged ($\Delta p_i > 0$), in percentage points, from a survey-weighted linear probability model. All characteristics shown enter jointly, along with month fixed effects. Horizontal bars indicate 95% confidence intervals based on standard errors clustered by respondent; filled markers indicate significance at the 5% level. The dashed line marks zero. Reference groups and increments for continuous variables are given in the labels. Non-White includes Asian, Black, Hispanic, and other respondents. The sample includes 8,567 respondent-wave observations; the outcome equals zero when $\Delta p_i \leq 0$. Borrowers with other or unknown DTI or an unknown credit score are excluded.

4 Conceptual Framework

The preceding evidence shows that the guarantee of approval reveals substantial refinancing demand that borrowers do not express under current conditions. We next develop a simple application model to interpret the discouragement wedge and guide the empirical analysis. The model clarifies how approval beliefs shape application probabilities under current conditions and guaranteed approval, and when approval risk weakens the response to refinancing incentives. It also shows how this lost response varies with perceived approval prospects. The framework provides a basis for distinguishing discouragement that remains under accurate approval beliefs from the additional discouragement associated with pessimism.

4.1 Application intentions and the access margin

Consider borrower i deciding whether to apply to refinance in the twelve months following the survey.[6] The value of a successful refinance is

$$V_i = v(\Delta r_i) + \varepsilon_i, \qquad v'(\Delta r) > 0. \tag{4}$$

The first term captures the refinancing incentive at the survey date: Δr_i is the rate gap, the difference between the borrower's current mortgage rate and the rate available on a new loan. The second term collects everything else that will determine the value of refinancing when the decision is made, such as subsequent movements in rates, a change in moving plans, or a need to extract equity. At the survey date, ε_i is uncertain. We denote the borrower's subjective distribution of ε_i by F_i and its density by f_i. Uncertainty about these future circumstances gives rise to probabilistic intentions.

Applying entails a cost $C_i > 0$, such as time, documentation, and fees incurred whether or not the application succeeds. The borrower assigns approval probability $q_i^{\text{subj}} \in (0, 1]$ to an application. We hold this belief fixed across the future value realizations in the simple model.[7] The borrower applies when

$$q_i^{\text{subj}} V_i > C_i \quad \Longleftrightarrow \quad V_i > \frac{C_i}{q_i^{\text{subj}}}. \tag{5}$$

Approval risk raises the value that refinancing must offer to justify applying. Relative to certain

[6] We collapse the twelve-month horizon into a single application decision; equivalently, the decision can be read as whether the borrower applies at any point during the horizon. All objects are measured at the survey date. We suppress the date subscript in the framework and restore it in the empirical specifications. For respondents interviewed in several waves, i indexes respondent-waves.

[7] The survey elicits the perceived chance that a refinance application over the next twelve months would be granted. We divide the reported percentage by 100 to obtain q_i^{subj}. The question is asked of a routed subsample, so exercises using this belief condition on its availability. If $q_i^{\text{subj}} = 0$, applying never pays its positive cost: $p_i^{\text{subj}} = 0$ and $\Delta p_i = p_i^G$.

approval, the hurdle rises by $C_i(1 - q_i^{\text{subj}})/q_i^{\text{subj}}$, so a borrower who puts her chance of approval at 50 percent applies only when refinancing is worth more than twice the application cost. Approval risk therefore deters by amplifying the cost of applying: if applying were costless, the borrower would apply whenever refinancing had positive value, however uncertain approval was.

We interpret the guarantee question as removing approval risk while leaving refinancing values and application costs unchanged. The two survey questions then elicit the probability that the value of refinancing clears the hurdle with and without approval risk:

$$p_i^{\text{subj}} \equiv \Pr_i\left(V_i > \frac{C_i}{q_i^{\text{subj}}}\right) = 1 - F_i\left(\frac{C_i}{q_i^{\text{subj}}} - v(\Delta r_i)\right), \tag{6}$$

$$p_i^{G} \equiv \Pr_i(V_i > C_i) = 1 - F_i(C_i - v(\Delta r_i))\,. \tag{7}$$

The within-borrower difference is therefore

$$\Delta p_i \equiv p_i^{G} - p_i^{\text{subj}} = \Pr_i\left(C_i < V_i \leq \frac{C_i}{q_i^{\text{subj}}}\right) \geq 0, \tag{8}$$

which we call the *discouragement wedge*. The wedge captures circumstances in which refinancing is worth the application cost under guaranteed approval but not worth risking an unsuccessful application. Figure 6(a) illustrates the probability mass between the two hurdles.

4.2 Two sources of discouragement

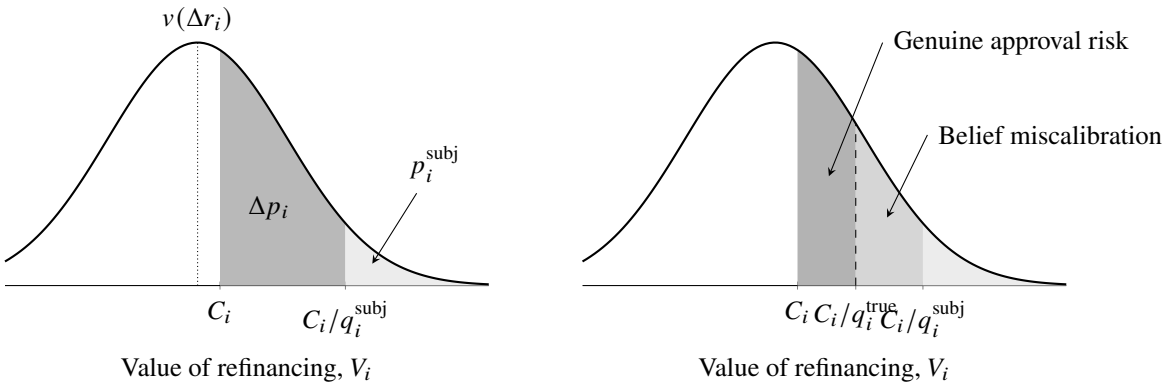
Approval risk can discourage refinancing even when beliefs are accurate. A borrower may correctly assess her approval prospects and still forgo applying because she would incur application costs without knowing whether she would obtain a loan.

To distinguish this discouragement from the effect of belief errors, let q_i^{true} denote the true approval probability and p_i^{true} the application probability in equation (6) evaluated under accurate approval beliefs, holding application costs and the distribution of refinancing values fixed. Adding and subtracting this probability gives

$$\underbrace{p_i^{G} - p_i^{\text{subj}}}_{\text{discouragement wedge}} = \underbrace{p_i^{G} - p_i^{\text{true}}}_{\text{approval risk}} + \underbrace{p_i^{\text{true}} - p_i^{\text{subj}}}_{\text{belief error}}. \tag{9}$$

The first component is the discouragement that remains under accurate approval beliefs. The second adds to discouragement when beliefs are pessimistic ($q_i^{\text{subj}} < q_i^{\text{true}}$) and offsets it when beliefs are optimistic ($q_i^{\text{subj}} > q_i^{\text{true}}$). Figure 6(b) illustrates the pessimistic case.

Correcting pessimistic beliefs addresses the second component. Reducing approval risk or application costs can also address discouragement that remains under accurate beliefs. Measuring the total wedge is therefore relevant to understanding refinancing demand regardless of whether borrowers misjudge their approval prospects. Section 6 examines these patterns by comparing borrowers' approval beliefs with the cHMDA benchmark.



(a) The discouragement wedge

(b) Genuine risk versus miscalibration

Figure 6: The access margin. Each panel plots the borrower's subjective density of the value of a successful refinance, $V_i = v(\Delta r_i) + \varepsilon_i$. She applies under her perceived approval chances when V_i exceeds C_i/q_i^{subj} and under guaranteed approval when V_i exceeds C_i. In panel (a), the light area is the ordinary application probability p_i^{subj}, the dark area is the wedge Δp_i, and together they form p_i^G. A better refinancing environment shifts the density to the right. In panel (b), the hurdle C_i/q_i^{true} that would apply with correct approval beliefs splits the wedge of a pessimistic borrower ($q_i^{\text{subj}} < q_i^{\text{true}}$) into the two components of equation (9). For an optimistic borrower ($q_i^{\text{subj}} > q_i^{\text{true}}$), C_i/q_i^{true} lies to the right of C_i/q_i^{subj}.

4.3 Refinancing incentives and lost pass-through

A larger rate gap raises the value of refinancing and shifts the distribution of V_i to the right. Both application probabilities therefore weakly increase. Their responses need not be equally large. Under the guarantee, an improvement generates an application whenever it moves refinancing value across C_i. Under current conditions, the same improvement must move value across C_i/q_i^{subj}. The difference between the two responses is

$$\frac{\partial \Delta p_i}{\partial \Delta r_i} = \frac{\partial p_i^G}{\partial \Delta r_i} - \frac{\partial p_i^{\text{subj}}}{\partial \Delta r_i}. \tag{10}$$

We call a positive difference *lost pass-through*: part of the response to a better refinancing opportunity appears under guaranteed approval but is absent from current intentions.

Intuitively, better rates can make refinancing worth pursuing if approval is certain, while leaving it insufficiently attractive to risk an unsuccessful application, we therefore expect some of the response to better rates to appear only under the guarantee. Appendix C provides the formal conditions and derivation.

Prediction 1 (Lost pass-through)**.** *Stated application probabilities rise with refinancing incentives, both under current conditions and under guaranteed approval. Under the conditions in Appendix C, the guaranteed response is larger, so the discouragement wedge rises with the rate gap.*

The same reasoning connects lost pass-through to perceived access. A borrower who considers approval unlikely requires a larger refinancing gain to justify applying, so better rates may raise her guaranteed intentions without inducing a comparable response under current conditions. At the other extreme, a borrower certain of approval faces the same hurdle in both scenarios: her wedge and lost pass-through are zero.

Prediction 2 (Where pass-through is lost)**.** *Among otherwise comparable borrowers, lost pass-through is larger when perceived approval is lower. It is zero for borrowers who are certain of approval.*

A final implication concerns the level of intentions. Approval beliefs shift the current hurdle but do not enter the guaranteed hurdle (which set approval beliefs to 1 by definition):

$$\frac{\partial p_i^G}{\partial q_i^{\text{subj}}} = 0, \qquad \frac{\partial \Delta p_i}{\partial q_i^{\text{subj}}} = -\frac{\partial p_i^{\text{subj}}}{\partial q_i^{\text{subj}}} = -\frac{C_i}{(q_i^{\text{subj}})^2} f_i\left(\frac{C_i}{q_i^{\text{subj}}} - v(\Delta r_i)\right) \leq 0. \tag{11}$$

If the guaranteed approval hypothetical eliminates the role of beliefs, we would expect to see that subjective beliefs about approval matter only for p_i^{subj} but not for p_i^G.

Section 5 examines these predictions in the data.

5 Hidden Demand and Refinancing Incentives

The framework connects approval concerns to the transmission of refinancing incentives into application intentions. This section tests its predictions. We first test Prediction 1 by relating current and guaranteed intentions to the common refinancing environment, and then Prediction 2 by allowing these responses to vary with perceived access. A final check asks whether approval beliefs are associated with current rather than guaranteed intentions.

5.1 Pass-through of the refinancing environment

Prediction 1 concerns a difference in responses: a better refinancing opportunity can reasonably raise guaranteed intentions more than current intentions. We summarize the common refinancing environment by the average rate gap, $\overline{\Delta r}_t$, assigning the same series to respondents surveyed in period t. Averaging reduces the direct dependence on any individual borrower's mortgage history, but the series can still reflect changes in sample composition and aggregate conditions. We therefore interpret the estimates as conditional associations with the refinancing environment rather than as responses to an exogenous interest-rate shock.

We run the following regressions for stated probabilities and the discouragement wedge.

$$y_{it} = \beta^y \overline{\Delta r}_t + X_{it}'\gamma^y + \epsilon_{it} \tag{12}$$

where $y \in \{p^{\text{subj}}, p^G, \Delta p\}$ and where X_{it} includes borrower's demographic and financial characteristics as controls and state fixed effects. The three regressions use the same sample and regressors, so $\beta^{\Delta p} = \beta^{p^G} - \beta^{p^{\text{subj}}}$ holds by construction. The coefficient in the Δp_{it} regression therefore measures lost pass-through directly, with its own standard error. We also report the *share of pass-through lost*, $\beta^{\Delta p}/\beta^{p^G}$.

Table 2 reports the regression results. Columns (1)–(3) use the full sample. Columns (4)–(6) restrict the sample to borrowers with a predicted approval probability of $\widehat{q}_{it} \geq 0.80$, indicating favorable observable approval prospects. Columns (7)–(9) instead restrict the sample to borrowers with a credit score above 680 and an LTV below 80 percent. These restrictions assess whether lost pass-through persists among borrowers with favorable observable approval prospects.

In column (1), p_{it}^{subj} is positively associated with the average rate gap, $\overline{\Delta r}_t$, with coefficient 1.45 and significant at 1% level. Thus, a one percentage point increase in the average rate gap is associated with a 1.45 percentage point increase in current refinancing intentions. Column (2) shows a larger association under guaranteed approval: the same increase in the average rate gap is associated with a 2.38 percentage point increase in the stated probability of applying p_{it}^G. Column (3) estimates the difference between these responses. The coefficient on the average rate gap is 0.93 and is statistically significant at the 1 percent level, consistent with Prediction 1. This implies that 39 percent of the estimated response under guaranteed approval is absent from current intentions.

Columns (4)–(9) show that lost pass-through persists among borrowers with favorable observable approval prospects. The share lost is 37 percent among borrowers with predicted approval of at least 80 percent and 34 percent among those with credit scores of at least 680 and loan-to-value ratios below 80 percent.

We note that time fixed effects cannot be included in equation (12) as $\overline{\Delta r}_t$ varies only over

time. Other aggregate changes may therefore contribute to the estimated associations. Taking the difference between the two stated probabilities mitigates this concern for $\beta^{\Delta p}$: differencing out aggregate shocks that affect current and approval-guaranteed intentions equally. As a robustness check, we replace the average rate gap with each borrower's own rate gap, Δr_{it}, and include time fixed effects. This specification exploits differences in rate gaps across borrowers surveyed at the same time, rather than changes in the aggregate refinancing environment, and therefore estimates a different relationship. Nevertheless, approval-guaranteed intentions again respond more strongly than current intentions, so the discouragement wedge increases with the borrower's own rate gap (Appendix D).

Table 2: Refinancing pass-through in the full and observably approvable samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Full			$\widehat{q}_i \geq 0.80$			Score ≥ 680, LTV < 80		
Dependent variable	p_{it}^{subj}	p_{it}^{G}	Δp_{it}	p_{it}^{subj}	p_{it}^{G}	Δp_{it}	p_{it}^{subj}	p_{it}^{G}	Δp_{it}
$\overline{\Delta r}_t$	1.45***	2.38***	0.93***	1.49***	2.38***	0.88***	1.53***	2.33***	0.79***
	(0.24)	(0.29)	(0.16)	(0.27)	(0.29)	(0.14)	(0.28)	(0.31)	(0.16)
Pass-through lost			39%			37%			34%
Borrower controls & state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,801	8,801	8,801	6,675	6,675	6,675	6,748	6,748	6,748
R^2	0.053	0.081	0.056	0.057	0.080	0.048	0.058	0.080	0.049

Notes: Each column reports a separate regression of equation (12). Coefficients on the average rate gap $\overline{\Delta r}_t$ are in percentage points of stated probability per percentage point of rate gap. Columns (1)–(3) use the full sample, columns (4)–(6) respondents with predicted approval $\widehat{q}_i \geq 0.80$, and columns (7)–(9) the prime sample, with a credit score of at least 680 and LTV below 80 percent. Share lost is $\beta_{\Delta p}/\beta_{p^G}$. All regressions include state fixed effects and borrower controls: self-reported credit score group, loan-to-value ratio, log loan amount, debt-to-income group, race and ethnicity, sex, age group, household income group, education, and employment status. Standard errors, two-way clustered by respondent and rate-lock quarter, are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

5.2 Where pass-through is lost

We test Prediction 2 using three separately elicited measures of perceived credit access. The qualifying-rate question is asked throughout the sample, regardless of respondents' stated probability of applying, and distinguishes perceptions about refinancing costs from the belief that refinancing is unavailable. We then examine expected rejection among respondents reporting low application probabilities and directly elicited approval beliefs among those reporting higher application probabilities.

Qualifying rate. We compare respondents' reported qualifying mortgage rates with their cHMDA-based predicted rates, $\hat{r}_{it}$. We interpret reported rates within 0.5 percentage points of the benchmark as indicating a near-benchmark assessment of the rate they could obtain. Rates more than 0.5 percentage points above the benchmark indicate pessimism about borrowing costs, while rates more than 0.5 points below indicate optimism. A fourth group reports that they "would not qualify at any rate." These borrowers perceive refinancing to be unavailable rather than expensive.

Let G denote these four groups. We allow each group to have its own level of application intentions and its own response to the average rate gap:

$$\begin{aligned} y_{it} = & \sum_{g \in G} \beta_g^y \left(\mathbb{1}\{g_{it} = g\} \times \overline{\Delta r}_t \right) \\ & + \sum_{g \in G} \lambda_g^y \mathbb{1}\{g_{it} = g\} + X_{it}' \gamma^y + \epsilon_{it}, \end{aligned} \tag{13}$$

For each outcome $y \in \{p^{\text{subj}}, p^G, \Delta p\}$, β_g^y measures the response to changes in the average rate gap $\overline{\Delta r}_t$ for group g. The group indicators allow outcome levels to differ across groups, captured by λ_g^y, and X_{it} includes borrower demographics and financial characteristics as controls, and state fixed effects.

Figure 7(a) plots the total responses for each group g, with 95% confidence intervals. Among respondents whose perceived qualifying rate lies within ±0.5 percentage points of the benchmark, a 1 percentage point increase in the average rate gap $\overline{\Delta r}_t$ is associated with increases of 1.29 percentage points in p^{subj} and 2.01 percentage points in p^G. Their discouragement wedge Δp therefore widens by 0.72 percentage points, similar in magnitude to the average response documented in Table 2.

Respondents with optimistic or pessimistic views of their qualifying rate have coefficients similar to those of the accurate group. Thus, the numerical qualifying-rate comparisons provide no evidence that greater price pessimism is associated with greater lost pass-through.

A different pattern emerges among respondents who believe they would not qualify at any rate. A one percentage point increase in the average rate gap is associated with increases of 1.45 percentage points in p^{subj} and 6.46 percentage points in p^G, implying a 5.01 percentage point widening of the discouragement wedge. Their current-intention response does not differ significantly from that of the reference group at the 10% level, while their guaranteed-intention and wedge responses are significantly larger at the 1% level.

These findings distinguish pessimism about refinancing terms from the belief that refinancing is unavailable. We find evidence of greater lost pass-through among respondents who believe they cannot qualify at any rate, but no statistically detectable increase among respondents reporting above-benchmark qualifying rates. This distinction supports an interpretation centered on perceived

approval barriers, consistent with Prediction 2.

Reasons for unlikely to apply. Among respondents with a low probability of applying to refinance ($p_{it}^{\text{subj}} < 10\%$), the SCE asks why they are unlikely to apply. We identify homeowners who report that they might need or want to refinance but would not apply because they expect rejection. These homeowners account for 5% percent of this subsample. We define two groups, $G = \{\text{Expected rejection, Other reasons}\}$, and estimate the same specification as above.

Figure 7(b) plots the estimated regression coefficients, following specification (13). Among respondents citing other reasons, application intentions respond only weakly to the average rate gap. A one percentage point increase in the gap is associated with increases of 0.08 percentage points in current application intentions (p^{subj}) and 0.56 percentage points in guaranteed-approval intentions (p^{G}). The discouragement wedge (Δp) therefore increases by only 0.47 percentage points. Among respondents citing expected rejection, current application intentions also respond weakly, increasing by 0.39 percentage points. However, guaranteed-approval intentions increase by 13.36 percentage points, and the discouragement wedge widens by 12.97 percentage points. Both the guaranteed-intention and wedge responses are more than 20 times those among respondents who do not cite rejection.

Because all respondents in this subsample report a low probability of applying, it is not surprising that their current intentions are only weakly associated to the rate gap. Under guaranteed approval, however, the two groups differ substantially. Respondents citing other reasons continue to respond weakly, consistent with the guarantee not affecting their intentions, since they did not report approval concerns as a reason for not applying. Among those citing expected rejection, by contrast, the guarantee reveals a strong response to better refinancing terms that is largely absent from their current intentions. Their low current intentions thus hide demand that would respond strongly to favorable refinancing opportunities if approval were guaranteed.

Approval beliefs among likely to apply. We then examine how respondents' subjective probability of approval, q_{it}^{sub}, affects responses to the average rate gap. As explained in Section 2, this question is asked only of respondents who report at least a 5 percent probability of applying to refinance ($p_{it}^{\text{subj}} \geq 5\%$).

To uncover the heterogeneity across approval beliefs, we run the following regression,

$$y_{it} = \beta^{y} \overline{\Delta r}_{t} + \delta^{y}\left(1 - q_{it}^{\text{subj}}\right) + \theta^{y}\left[\overline{\Delta r}_{t} \times \left(1 - q_{it}^{\text{subj}}\right)\right] + X_{it}'\gamma^{y} + \epsilon_{it}. \tag{14}$$

where $y \in \{p^{\text{subj}}, p^{G}, \Delta p\}$ and X_{it} includes borrower demographic and financial characteristics and state fixed effects. We express approval beliefs as perceived denial risk, $1 - q_{it}^{\text{subj}}$, so higher values

indicate greater doubt about approval. The response to the average rate gap is $\beta^y + \theta^y(1 - q_{it}^{\text{subj}})$. Thus, β^y measures the response among borrowers who believe approval is certain, while θ^y measures how this response changes as perceived denial risk rises.

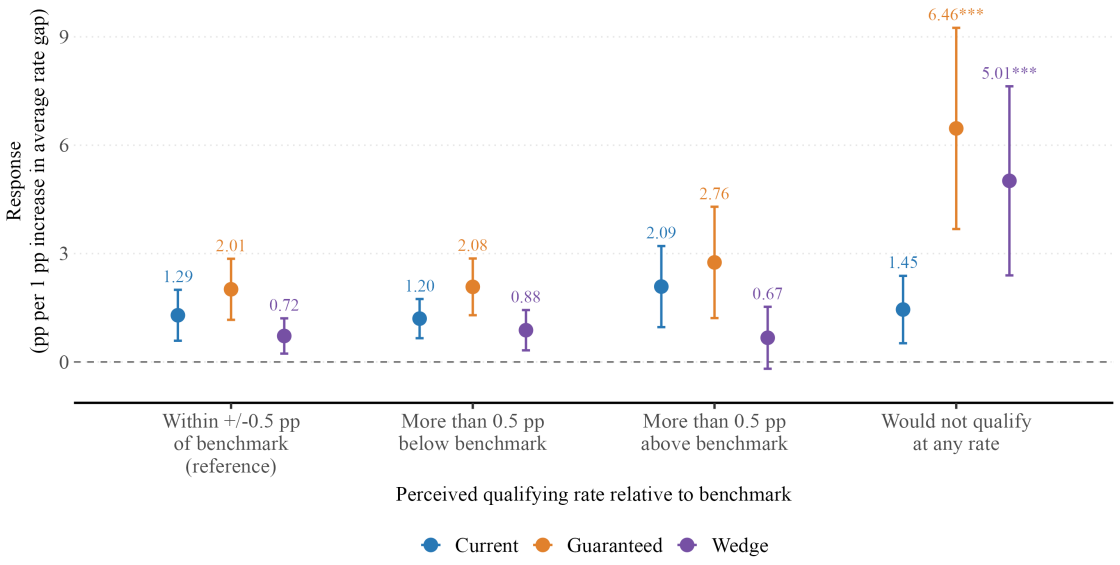
Prediction 2 motivates two tests. First, $\beta^{\Delta p} = 0$: for borrowers already certain of approval, the guarantee removes no perceived barrier. Their current and guaranteed intentions should therefore coincide at every rate gap, leaving no lost pass-through. Second, $\theta^{\Delta p} > 0$: lost pass-through should increase with perceived denial risk. Borrowers who doubt approval require larger refinancing gains to justify incurring application costs that they would bear even if rejected. Better refinancing terms may therefore make applying attractive under guaranteed approval while leaving it unattractive under current conditions. Greater perceived denial risk can thus leave more of the response to better terms visible only under the guarantee.

Figure 7(c) reports the implied total responses to the average rate gap at certain approval and at the 25th percentile of approval beliefs ($q_{it}^{\text{subj}} = 0.65$). The lower quartile provides a comparison below certainty without evaluating responses at zero approval, a boundary of the support.

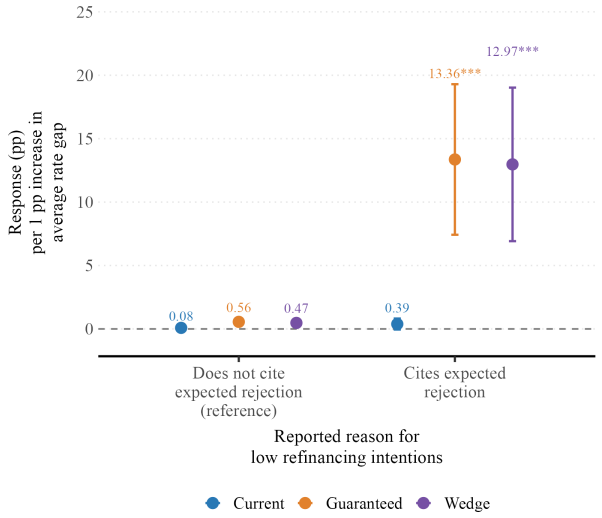
Lost pass-through is close to zero under certain approval and rises with doubt. For a borrower certain of approval, a one percentage point increase in the average rate gap is associated with a widening of the wedge of only 0.23 percentage points, statistically indistinguishable from zero and consistent with the prediction. Current and guaranteed intentions both rise, by similar amounts of 2.32 and 2.55 percentage points, respectively. These borrowers therefore respond to the rate environment, but their current intentions respond as much as they do under guaranteed approval.

On the other hand, lost pass-through increases as perceived approval becomes less certain. Each ten percentage point increase in perceived denial probability is associated with an additional 0.26 percentage point response of the wedge to the rate gap, significant at the 10% level. At the lower quartile of approval beliefs, about 35 percent of the estimated response under guaranteed approval is absent from current intentions. This lost pass-through is greater than at certain approval, with the difference significant at the 10 percent level, consistent with Prediction 2. The point estimates show a similar pattern among borrowers with favorable observable approval prospects.

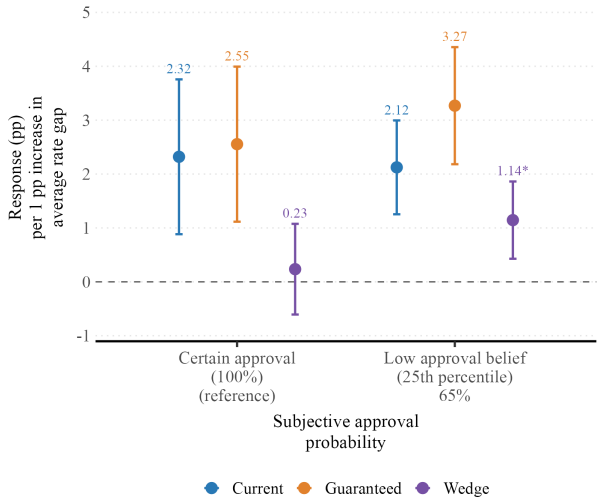
As a complementary check on levels, we relate approval beliefs to the two probabilities of applying. The framework predicts that beliefs affect current intentions but not guaranteed intentions, which fix approval at certainty. If beliefs instead proxied for stronger demand or larger gains from refinancing, they would also predict guaranteed intentions. Consistent with the framework, greater perceived denial risk is associated with lower current probabilities of applying and a larger wedge, while its association with guaranteed-probabilities of applying is statistically insignificant.



(a) Perceived qualifying rate



(b) Expected rejection



(c) Subjective approval probability

Figure 7: Refinancing pass-through by perceived access to mortgage credit.

Notes: Dots show the responses of current intentions (p^{subj}), guaranteed-approval intentions (p^{G}), and their wedge (Δp) to a one percentage point increase in the average rate gap. Panel (a) groups respondents by their perceived qualifying rates relative to the cHMDA-based benchmark. Panel (b) distinguishes respondents asked about reasons for low refinancing intentions by whether they cite expected rejection. Panel (c) evaluates the continuous approval-belief specification at certain approval (100%) and at the sample's 25th percentile of approval beliefs (65%), among respondents with $p^{\text{subj}} \geq 5$. Regressions include borrower controls and state fixed effects. Bars show 95% confidence intervals using standard errors two-way clustered by respondent and rate-lock quarter. Stars test differences for the same outcome relative to the within-±0.5 pp group in Panel (a), respondents who do not cite expected rejection in Panel (b), and certain approval in Panel (c): $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6 Approval Risk and Pessimism Relative to the Benchmark

We now turn from the response to refinancing incentives to the level of hidden demand. The framework distinguishes discouragement that remains under accurate approval beliefs from the additional discouragement associated with pessimism. We examine this distinction using the cHMDA approval benchmark: first comparing beliefs among discouraged and other borrowers, then examining suppression among borrowers whose beliefs are close to or below the benchmark.

6.1 Beliefs and the approval benchmark

The framework distinguishes approval risk from belief errors, but borrowers' true approval probabilities are unobserved. We therefore use the cHMDA benchmark $\widehat{q}_i$ from equation (2), which predicts approval from characteristics observed in both datasets. This provides a reference for assessing whether borrowers view their approval prospects more or less favorably than their observable characteristics would suggest.

$$\underbrace{1 - q_i^{\text{subj}}}_{\text{perceived denial risk}} = \underbrace{1 - \widehat{q}_i}_{\text{predicted denial risk}} + \underbrace{\widehat{q}_i - q_i^{\text{subj}}}_{\text{approval-belief gap}} \tag{15}$$

A positive belief gap indicates pessimism relative to the benchmark, while a negative gap indicates optimism. Matching the benchmark need not imply certain approval: borrowers can agree with its prediction and still perceive a chance of rejection that discourages applying. This is captured by the "predicted denial risk" term of equation (15).

We first examine whether discouraged borrowers report lower approval beliefs q_{ij}^{subj} at comparable predicted prospects $\widehat{q}_i$. Figure 8 shows binned averages and fitted relationships between subjective and predicted approval for respondents with positive and nonpositive discouragement wedges. Appendix Table D4 reports the regression estimates.

A one percentage point increase in predicted approval is associated with a 0.48 percentage point increase in subjective approval beliefs among respondents with a nonpositive wedge and a 0.46 percentage point increase among those with a positive discouragement wedge ($\Delta p_i > 0$). We do not reject equality of these slopes ($p = 0.728$). Approval beliefs therefore reflect the observable prospects captured by our benchmark in both groups. However, discouraged respondents report lower approval beliefs at comparable predicted prospects. At predicted approval of 80 percent, fitted subjective approval is 70.9 percent among discouraged respondents, compared with 81.0 percent among other respondents—a difference of 10.1 percentage points (SE 1.52; $p < 0.01$). The pattern is consistent with discouragement being associated primarily with lower approval beliefs

rather than a weaker relationship between beliefs and observable approval prospects.

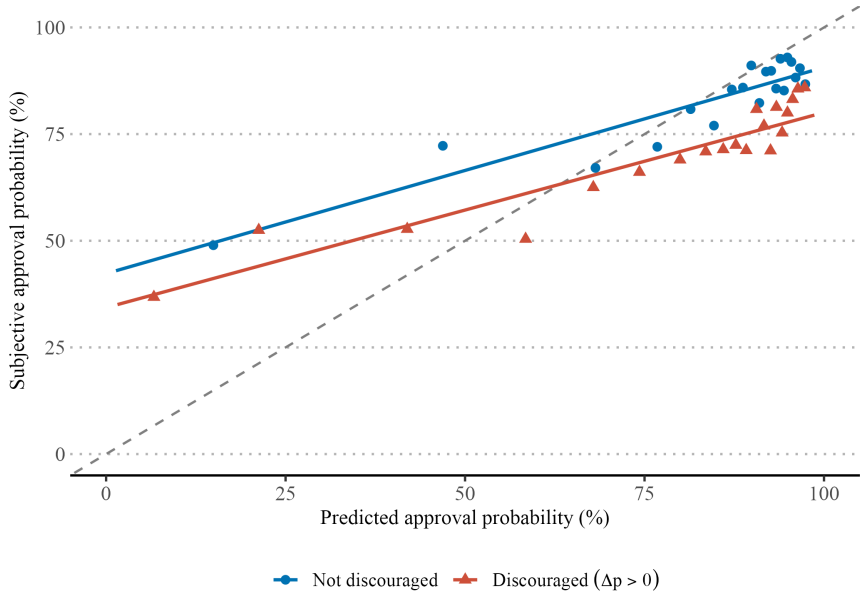


Figure 8: Approval beliefs and predicted approval by discouragement

Notes: The sample comprises respondents reporting an approval belief in the rate-linked analysis sample (N = 3,039 respondent-wave observations). Blue circles and red triangles show survey-weighted averages of subjective and predicted approval probabilities within 20 quantile bins of predicted approval, constructed separately for respondents with nonpositive ($\Delta p_i \leq 0$) and positive ($\Delta p_i > 0$) discouragement wedges. Bins with fewer than ten observations are omitted. Solid lines are fitted values from a pooled survey-weighted regression of subjective approval beliefs on predicted approval, an indicator for a positive wedge, and their interaction. Predicted approval is centered at 80 percent and scaled per ten percentage points. The dashed line is the 45-degree line.

We need to be cautious about whether we can interpret this evidence as belief errors. Borrowers may have private information about their approval prospects that $\widehat{q}_i$ does not capture. Moreover, the cHMDA benchmark is estimated among actual applicants, while we have potential applicants in SCE samples. Applicants and nonapplicants may differ in approval-relevant characteristics that the benchmark does not observe, even conditional on the included predictors. In Appendix B.5, we validate the benchmark using realized approval among survey respondents who apply. We provide an additional check in Appendix B.4 using recommendations from automated underwriting systems (AUS). The same borrower characteristics drive both our approval predictions and AUS recommendations, supporting the benchmark's ability to capture the lenders' relevant underwriting criteria.

6.2 Discouragement near and below the benchmark

We next examine whether refinancing demand remains suppressed when approval beliefs are close to the benchmark, and whether pessimism is associated with additional suppression. We focus

on respondents who report an approval belief and have high predicted approval ($\widehat{q}_i \geq 0.80$). This restriction concentrates the comparison on homeowners with strong observable approval prospects and on the range in which the benchmark is best calibrated (Appendix B.5).

Figure 9 groups respondents by their subjective approval probability relative to the benchmark. For each group, we plot the *suppression rate* $100\,\overline{\Delta p}_g / \overline{p^G}_g$, where the bars denote the means of the survey-weighted group. This measures the share of stated demand under guaranteed approval that is absent under current conditions. Normalizing by guaranteed intentions accounts for differences across groups in how much demand could be held back. Appendix Table D5 reports the underlying means.

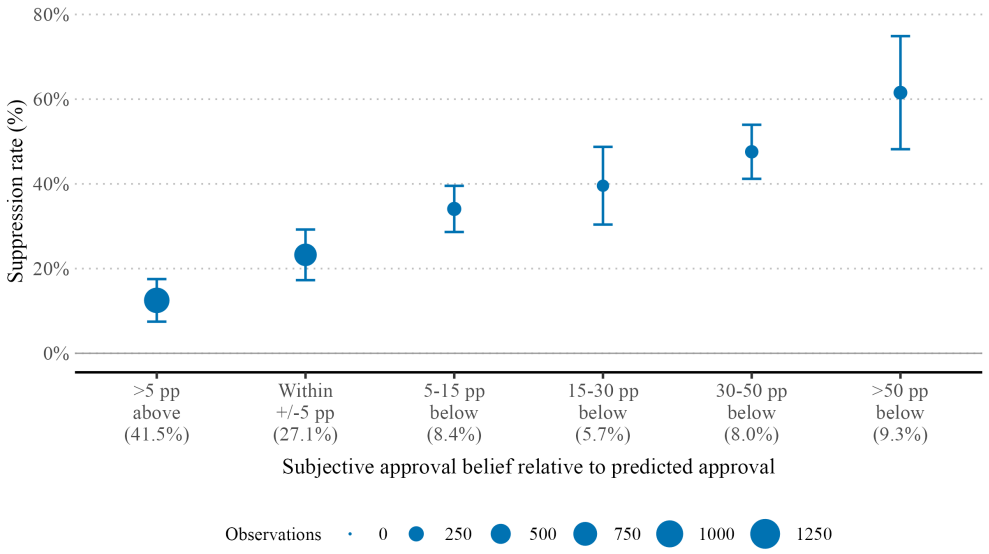


Figure 9: Refinancing demand suppression and approval beliefs

Notes: The sample comprises respondents who report an approval belief and have predicted approval $\widehat{q}_i \geq 0.80$ (N = 2,266 respondent-wave observations). Groups compare subjective approval beliefs, q_i^{subj}, with predicted approval, $\widehat{q}_i$. Dots show the suppression rate, $100\,\overline{\Delta p}_g / \overline{p^G}_g$, where $\Delta p_i = p_i^G - p_i^{\text{subj}}$ and the bars denote survey-weighted group means. This is the share of stated demand under guaranteed approval that is absent under current conditions. Dot area is proportional to the unweighted number of observations in each group; the sample shares are shown on the x-axis. Vertical bars show 95% confidence intervals using standard errors clustered by respondent. The within-benchmark group includes both endpoints, ±5 percentage points. Respondents reporting certain approval are assigned according to their actual belief gap.

Among respondents whose approval beliefs are within five percentage points of the benchmark, 23.2 percent of stated demand under guaranteed approval is absent under current conditions. Suppression rises to 34.1 percent for beliefs 5–15 percentage points below the benchmark and reaches 61.5 percent for shortfalls exceeding 50 points. In contrast, respondents whose beliefs exceed the benchmark by more than five percentage points have a suppression rate of 12.5 percent. This pattern is consistent with pessimistic approval beliefs compounding the discouragement associated

with approval risk.

Respondents whose approval beliefs fall more than five percentage points below the benchmark make up 31.4 percent of the sample but account for about two-thirds of the aggregate discouragement wedge (Appendix Table D5). Hidden demand is therefore concentrated among borrowers with pessimistic approval beliefs. To quantify the additional suppression associated with these beliefs, we assign each below-benchmark group the near-benchmark suppression rate while holding its size and guaranteed intentions fixed. This descriptive standardization reduces the average discouragement wedge from 9.0 to 6.1 percentage points, a reduction of 32.4 percent (Appendix Table D7).[8]

The evidence is therefore consistent with pessimism amplifying approval-related discouragement, while substantial suppression remains among borrowers whose beliefs are close to the benchmark. The framework explains why discouragement can persist even under accurate beliefs: applying is costly and approval remains uncertain. Together, the model and evidence suggest that better information alone may not fully release hidden demand, and that reducing approval risk or application costs may also matter.

7 Conclusion

Approval concerns hold back stated refinancing demand and weaken its response to better terms, even among borrowers with strong observable approval prospects. Guaranteed approval nearly doubles the average stated probability of applying. Better refinancing terms raise this probability about 40 percent less under current conditions than under guaranteed approval, and the discouragement wedge is larger where potential rate savings are greater.

The belief comparisons are consistent with pessimism amplifying discouragement. Yet borrowers whose beliefs are close to the approval benchmark still hold back about a quarter of the demand they report under guaranteed approval. The framework explains why: even borrowers who accurately assess their prospects may forgo applying because they must incur costs without knowing whether they will obtain a loan. Approval risk thus offers one interpretation of the costs of acting inferred from refinancing inaction.

These findings matter for both the measurement of credit access and the transmission of lower rates to households. Application records miss the additional demand held back by approval concerns, including among borrowers who eventually apply. Better information about approval

[8] Appendix D.4 describes the calculation. Each below-benchmark group is assigned the reference suppression rate, $s_0 \simeq 0.232$, while the near- and above-benchmark groups retain their observed wedges. Interpreting this standardization as the effect of correcting pessimistic beliefs requires comparable application costs and refinancing values across groups at similar predicted risk, and an adequate benchmark for approval prospects. The exercise does not measure the effect of bringing all respondents' beliefs to the benchmark.

prospects may release some hidden demand, while reducing approval risk or application costs may also be necessary to address discouragement that persists under accurate beliefs.

Our evidence rests on stated counterfactuals and a benchmark that may omit approval-relevant private information. Although stated intentions predict subsequent applications, behavior under guaranteed approval remains unobserved. Experiments that vary approval information, approval risk, or application costs could establish how these mechanisms translate into actual refinancing.

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A Data

A.1 Sample and Routing

Table A1: Analysis Sample and Survey Routing

Sample or subsample	Observations (share)
Panel A. Analysis sample	
All observations	**8,988 (100.0%)**
Panel B. Survey routing: mutually exclusive groups	
Beliefs only	1,680 (18.7%)
Reasons only	5,943 (66.1%)
Both beliefs and reasons	1,365 (15.2%)
Panel C. Question availability and responses	
Shown approval-belief question	3,045 (33.9%)
Recorded subjective approval probability	3,039 (33.8%)
Shown reasons questions	7,308 (81.3%)
Qualifying-rate question: any recorded response	8,946 (99.5%)
Numeric qualifying rate	8,650 (96.2%)
Would not qualify at any rate	296 (3.3%)
No recorded response	42 (0.5%)

Notes: The unit of observation is a respondent-wave. The analysis sample covers 2017–2025 and requires observed probabilities of applying under current conditions, p_i^{subj}, and under guaranteed approval, p_i^G, together with the selected borrower-specific predicted refinancing rate gap. Panel B classifies respondents by which refinance questions they were shown. Shares are relative to the full sample and may not sum exactly because of rounding.

Table A2: Number of survey waves per respondent

Waves per	Respondents		Respondent-waves	
respondent	N	Share (%)	N	Share (%)
1	812	20.3	812	9.0
2	1,369	34.3	2,738	30.5
3	1,806	45.2	5,418	60.3
4	5	0.1	20	0.2
Total	3,992	100.0	8,988	100.0

Notes: Rate-linked analysis sample. A wave is a distinct survey month in which the respondent appears in the sample. The Credit Access module is fielded every four months, the Housing module once a year. Respondent-waves for each row equal the number of waves times the number of respondents.

A.2 Summary Statistics SCE

Table A3: Sociodemographic characteristics: SCE mortgage holders

	Share (%)		Share (%)		Share (%)
Age		*Race and ethnicity*		*Employment status*	
18–34	17.6	White	80.7	Employed	78.6
35–54	49.9	Black	5.1	Looking for work	1.4
55+	32.6	Hispanic	6.4	Retired	14.6
Household income		Asian	3.3	Student	0.4
Under $30k	4.3	Other	4.5	Out of labor force	4.6
$30–60k	18.0	Female	43.0	Other	0.5
$60–100k	30.4	College degree	78.4		
$100k+	47.3	Married	74.6		

Notes: The sample contains 8,988 respondent-wave observations from 2017–2025, representing 3,992 unique respondents. Shares are percentages of respondent-wave observations and may not sum to 100 because of rounding.

Table A4: Summary statistics: SCE mortgage holders

Panel A: Housing and mortgage characteristics

Variable	Mean	Variable	Mean
Purchase price ($)	257,600	Initial loan amount ($)	211,971
Current home value ($)	377,217	Outstanding balance ($)	181,970
Expected home value, 1 year ($)	386,903	Monthly payment ($)	1,488
LTV, current value (%)	53.9	Current interest rate (%)	3.9
LTV, purchase price (%)	78.2	Ever refinanced (%)	55.3

Panel B: Credit score distribution

	< 620	620–679	680–719	720–760	> 760	Don't know
Share (%)	2.94	5.84	9.43	19.51	59.22	3.05

Notes: The sample contains 8,988 respondent-wave observations from 2017–2025. Dollar values are sample means rounded to the nearest dollar. Current and expected home values are respondents' beliefs. Loan-to-value ratios and refinancing-history means are reported in percent. Credit score is self-reported; shares use all 8,988 observations as the denominator. Shares may not sum exactly because of rounding.

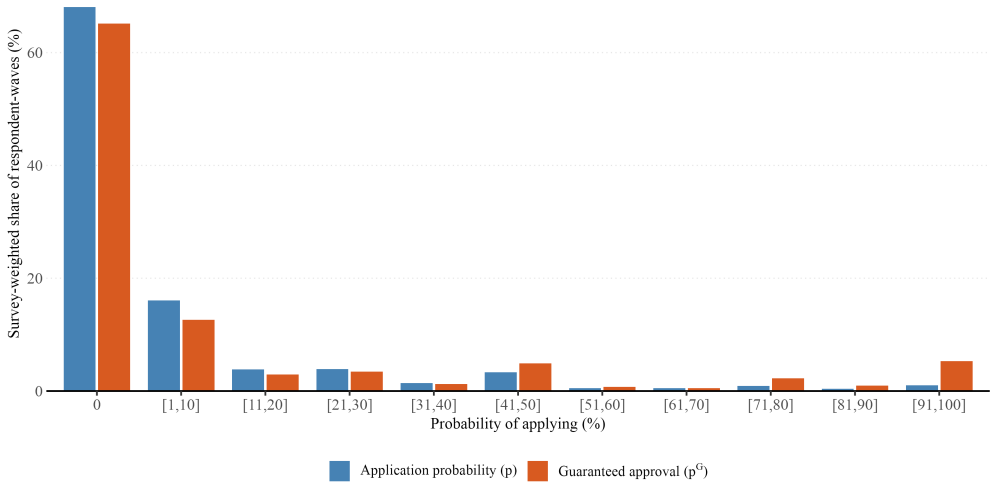
Table A5: Refinancing applications and acceptances by year

	2017	2018	2019	2020	2021	2022	2023	2024	2025	All years
Application rate (%)	10.3	8.0	6.7	10.8	25.0	14.4	4.0	1.0	2.5	9.7
Acceptance rate (%)	8.2	6.2	4.7	9.9	22.2	13.3	3.2	0.9	1.5	8.2
Acceptance rate among applicants (%)	79.7	77.6	69.5	91.0	88.7	92.0	79.7	88.7	58.0	84.6
Respondent-waves (N)	1,070	1,029	1,062	956	1,056	1,103	991	911	810	8,988
Applicants (N)	113	86	70	119	277	161	35	11	19	891

Notes: Survey-weighted means from the SCE; the year is the survey year. Application rate is the share of respondents who report having applied to refinance in the previous 12 months. Acceptance rate is the share who report an accepted application in that period, as a share of all respondents. Acceptance rate among applicants is the share of applicants whose application was accepted. All years pools every respondent-wave in the sample; it is not the average of the yearly values. Sample sizes are unweighted counts. Acceptance rates among applicants for 2023–2025 rest on few applicants. Baseline sample.

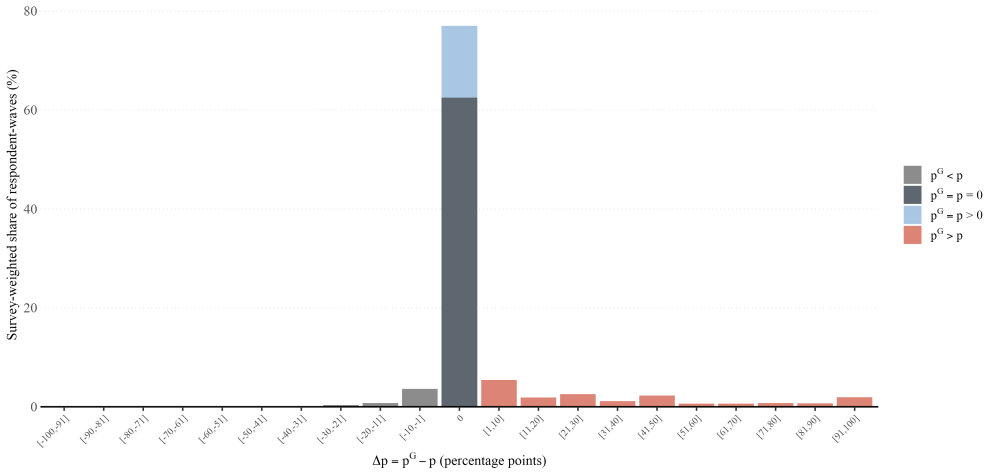
A.3 Distribution of the wedge

Figure A1: Probabilities of applying under current conditions and under guaranteed approval



Notes: Survey-weighted distributions of the stated probability of applying to refinance over the next twelve months under current conditions, p_{it}^{subj}, and under guaranteed approval, p_{it}^{G}. Shares are percentages of all respondent-waves, so each distribution sums to 100 percent. The first bar is the share reporting exactly zero; the remaining bins are ten percentage points wide.

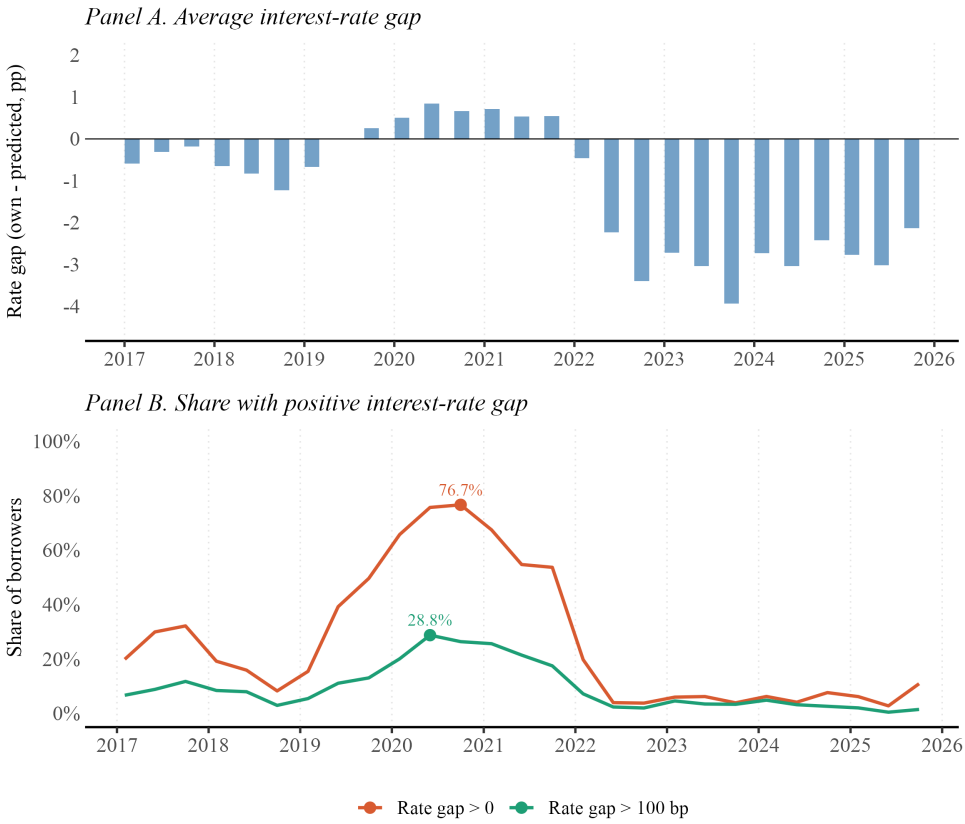
Figure A2: Distribution of the discouragement wedge



Notes: Survey-weighted distribution of the discouragement wedge.

A.4 The rate gap

Figure A3: Evolution of the interest-rate gap



Notes: Panel A plots the average interest-rate gap, defined as the borrower's own mortgage rate minus the predicted rate, in percentage points. Panel B plots the share of borrowers with a positive gap (red) and with a gap above 100 basis points (green). The share with a positive gap peaks at 75.6 percent in mid-2020, while the share with a gap above 100 basis points peaks at 26.5 percent in late 2020. Each bar/point is a survey wave.

B cHMDA Prediction Models

This appendix describes the two prediction models summarized in Section 2.2: the estimation samples, the harmonization of predictors between cHMDA and the SCE, estimation and out-of-sample fit, the characteristics that drive the predictions, and a validation of the approval benchmark on SCE respondents who apply.

B.1 Estimation samples

Both models are estimated on conventional, owner-occupied, first-lien, 30-year refinance applications from 2017–2025. We exclude reverse mortgages, open-end lines of credit, and business or commercial loans, and keep applications that were originated, approved but not accepted, or denied. Applications that were withdrawn, closed for incompleteness, or purchased by the reporting institution are excluded, since their outcome does not reflect a lender's underwriting decision.

The approval model uses all these applications. Its outcome equals one if the application was originated or approved but not accepted, and zero if it was denied. The spread model uses the subset of applications with a reported APR–APOR spread. Its outcome is that spread, in percentage points.

B.2 Predictors and harmonization

Both models use the same predictors, each chosen because it can be measured in both cHMDA and the SCE:

- credit score;
- loan-to-value (LTV);
- log loan amount;
- household income;
- debt-to-income (DTI);
- log property value;
- race, sex, age, and state;
- application year-month indicators.

Categorical predictors use the same category definitions and orderings in both data sets, so that the fitted models can be applied to SCE respondents without modification.

B.3 Estimation and out-of-sample fit

We estimate both models with LightGBM, a gradient-boosted decision-tree algorithm. It captures nonlinear relationships and interactions among borrower, loan, property, geographic, and time characteristics without imposing a parametric form. To evaluate out-of-sample performance, we randomly split each sample into an 80 percent training sample and a 20 percent test sample. We

then re-estimate each model on the full sample and apply it to the SCE to obtain respondent-specific predictions. Table B1 reports fit in the test sample.

Table B1: Out-of-sample fit of the cHMDA prediction models

	Rate spread	Approval
Outcome	APR − APOR (pp)	1{approved}
Out-of-sample R^2	0.45	0.47
Area under the ROC curve (AUC)	–	0.89

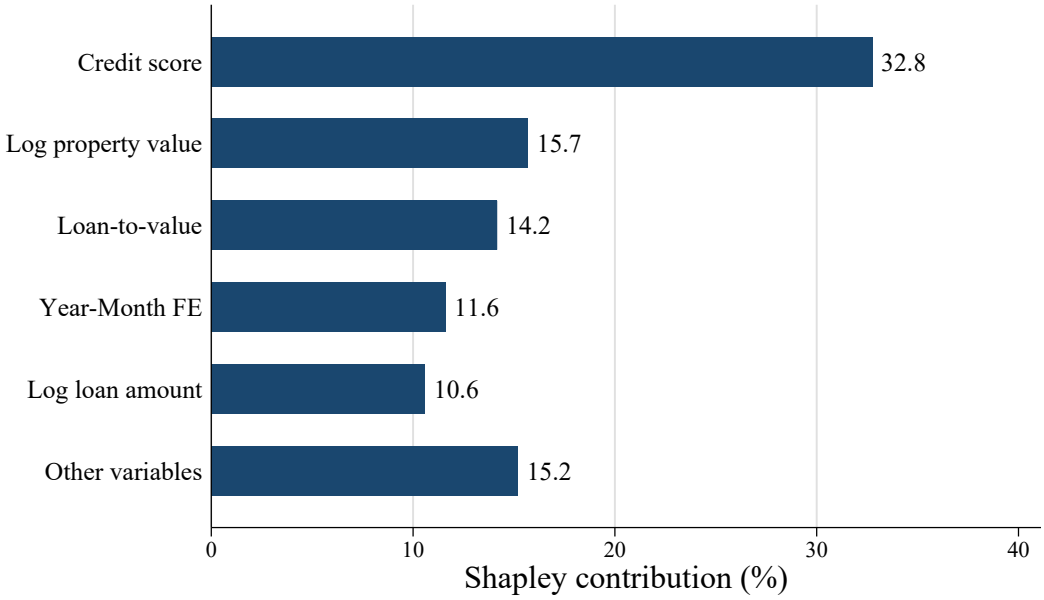
Notes: Fit statistics are computed on a random 20 percent test sample of the cHMDA estimation sample; the models are trained on the remaining 80 percent. The AUC is the probability that the model assigns a higher predicted approval probability to a randomly chosen approved application than to a randomly chosen denied one.

B.4 Which characteristics drive the predictions

To assess which characteristics account for the models' predictive power, we decompose each model's R^2 using a Shapley decomposition. For each predictor, we measure how much it improves predictive R^2, averaging over randomly sampled orders in which the predictors enter the model, and report its share of the total improvement over a model with no predictors. The shares sum to 100 percent.

Figure B1 shows the decomposition for the spread model. Credit score is the largest contributor, with 32.8 percent of the gain, followed by log property value (15.7 percent), LTV (14.2 percent), application year-month (11.6 percent), and log loan amount (10.6 percent). Income, state, race, age, DTI, and sex together account for about 15 percent.

Figure B1: Predictor contributions to refinancing rate spreads

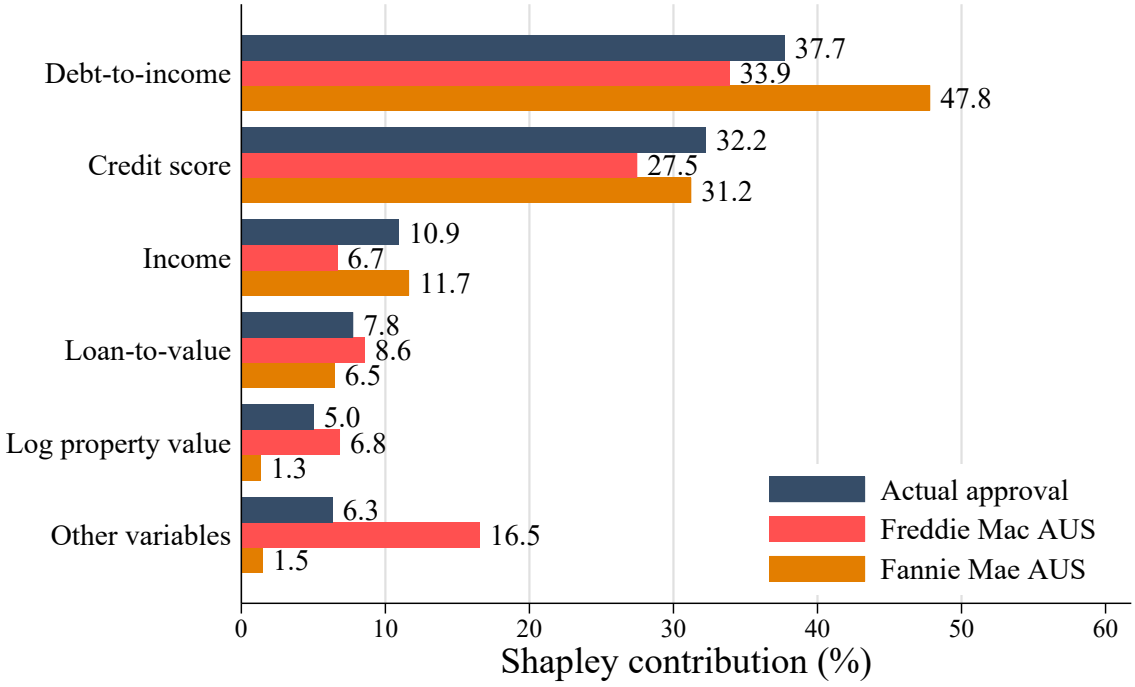


Notes: Bars report percentage shares of the Shapley decomposition of the spread model's R^2 improvement over a model with no predictors. The outcome is the APR–APOR spread. The five largest individual contributions are shown; "Other variables" combines the remaining predictors. Shares sum to 100 percent, subject to rounding.

Approval is driven by different characteristics. Figure B2 shows that DTI is the largest contributor to predicting approval, with 37.7 percent of the gain, followed by credit score (32.3 percent), income (10.9 percent), LTV (7.8 percent), and log property value (5.0 percent). DTI accounts for only 0.8 percent of the gain in the spread model. The models therefore separate the characteristics that determine whether a borrower qualifies from those that determine the price she pays.

As an external check, we compare the approval model with the recommendations of the automated underwriting systems (AUS) that lenders use to assess applications before making a final decision: Fannie Mae's Desktop Underwriter (DU) and Freddie Mac's Loan Product Advisor (LPA). We define a positive recommendation as Approve/Eligible for DU and Accept for LPA, code other explicit recommendations as zero, and exclude errors, incomplete or invalid results, and other non-decisions. Using the same predictors, we estimate separate LightGBM models for positive AUS recommendations and apply the same decomposition. DTI and credit score are again the two largest contributors: 33.9 and 27.5 percent of the gain for LPA, and 47.8 and 31.2 percent for DU. Income and LTV also contribute to all three outcomes. Although the exact shares differ, the approval model relies on the same characteristics as the underwriting systems.

Figure B2: Predictor contributions to refinancing approval and AUS recommendations



Notes: Bars report percentage shares of the Shapley decomposition of each model's R^2 improvement over a model with no predictors. The outcomes are actual lender approval and positive recommendations from Freddie Mac's and Fannie Mae's automated underwriting systems. The five named predictors are shown individually; "Other variables" combines the remaining predictors. Shares sum to 100 percent for each model, subject to rounding.

B.5 Validation on SCE applicants

The approval model is estimated on cHMDA applications. To check how well it predicts outcomes in the population we study, we compare predicted approval with realized outcomes for SCE respondents whom we observe applying to refinance in a later wave. We sort these respondents into five equal-sized bins of $\widehat{q}_i$. Within each bin, we compare mean predicted approval with the share whose application was accepted (Table B2).

Where predicted approval is high, the benchmark is close to realized outcomes. Across the top four bins, predicted approval averages 91.8 percent and realized acceptance 90.6 percent, and no bin differs by more than about 5 points. In the bottom bin, realized acceptance exceeds predicted approval by 18 points, 62.5 against 44.3 percent. Two features of the comparison may contribute to this gap. First, cHMDA records each application separately, whereas the SCE records whether the respondent's application was accepted. A borrower who is denied by one lender and approved by another therefore counts as a denial in cHMDA but as an acceptance in the survey, which matters most where denials are common. Second, when characteristics are self-reported with error,

predictions at the extremes are too extreme, so realized outcomes in the lowest bin are pulled toward the mean. This check is informative only about borrowers who apply; Section 4.2 discusses what it implies for those who do not.

Table B2: Predicted approval and realized acceptance among SCE applicants

Bin of $\widehat{q}_i$	Observations	Predicted approval	Realized acceptance	Difference
1 (lowest)	180	44.3	62.5	18.1
2	179	84.8	88.4	3.7
3	179	91.6	89.0	−2.5
4	179	94.3	89.0	−5.3
5 (highest)	179	96.6	96.0	−0.6
Bins 2–5	716	91.8	90.6	−1.2

Notes: SCE respondents observed applying to refinance in a later wave, sorted into five equal-sized bins of predicted approval $\widehat{q}_i$. Predicted approval is the bin mean of $\widehat{q}_i$; realized acceptance is the share of these respondents whose application was accepted. Both are in percent; the difference is realized minus predicted, in percentage points. The last row pools bins 2–5.

C Framework Details

This appendix derives the conditions behind Predictions 1 and 2. From equations (6) and (7),

$$\frac{\partial p_i^{\text{subj}}}{\partial \Delta r_i} = v'(\Delta r_i)\, f_i\!\left(\frac{C_i}{q_i^{\text{subj}}} - v(\Delta r_i)\right), \qquad \frac{\partial p_i^{G}}{\partial \Delta r_i} = v'(\Delta r_i)\, f_i(C_i - v(\Delta r_i))\,. \tag{C.1}$$

Each response is proportional to the density at the relevant hurdle. Define the pass-through ratio

$$\pi_i \equiv \frac{\partial p_i^{\text{subj}}/\partial \Delta r_i}{\partial p_i^{G}/\partial \Delta r_i} = \frac{f_i\!\left(C_i/q_i^{\text{subj}} - v(\Delta r_i)\right)}{f_i(C_i - v(\Delta r_i))}. \tag{C.2}$$

Lost pass-through is then

$$\frac{\partial \Delta p_i}{\partial \Delta r_i} = (1 - \pi_i)\,\frac{\partial p_i^{G}}{\partial \Delta r_i}, \tag{C.3}$$

which is positive exactly when $\pi_i < 1$.

Certain approval. When $q_i^{\text{subj}} = 1$, the two hurdles coincide and $\pi_i = 1$, so Δp_i and its response to Δr_i are zero for any distribution of future values.

Lost pass-through. Suppose the shocks ε_i are symmetric and unimodal, with their center absorbed into $v(\cdot)$. The density then declines with distance from $v(\Delta r_i)$, so $\pi_i < 1$ exactly when the guaranteed hurdle lies closer to the center of the distribution than the current hurdle. By symmetry, this condition can be written in terms of the two survey responses:

$$\frac{\partial \Delta p_i}{\partial \Delta r_i} > 0 \quad \Longleftrightarrow \quad p_i^{\text{subj}} + p_i^G < 1. \tag{C.4}$$

This is the condition behind Prediction 1.

Perceived access. Because $p_i^{\text{subj}} \leq p_i^G$, condition (C.4) implies $p_i^{\text{subj}} < 1/2$. The current hurdle then lies above the center of the distribution, where the density is decreasing, so that

$$\frac{\partial \pi_i}{\partial q_i^{\text{subj}}} = -\frac{C_i}{\left(q_i^{\text{subj}}\right)^2} \frac{f_i'\left(C_i/q_i^{\text{subj}} - v(\Delta r_i)\right)}{f_i(C_i - v(\Delta r_i))} \geq 0. \tag{C.5}$$

Since $\partial p_i^G / \partial \Delta r_i$ does not depend on q_i^{subj}, lost pass-through is larger when perceived approval is lower, holding costs, refinancing values, and F_i fixed. This is Prediction 2. Because $v'(\Delta r_i)$ cancels from π_i, groups that differ in how strongly the value of refinancing responds to rates can be compared through the share of pass-through lost, $1 - \pi_i$.

D Additional Results and Robustness

D.1 Probabilities of applying versus applications

Table D1: Stated intentions and subsequent refinancing applications

	Linear		Spline		Bins	
	(1)	(2)	(3)	(4)	(5)	(6)
Stated probability (per 10 pp)	1.29***	1.32***	0.68***	0.67***		
	(0.23)	(0.24)	(0.23)	(0.24)		
(Stated probability − 50)$^+$ (per 10 pp)			2.71**	2.88**		
			(1.15)	(1.18)		
Stated probability: 1–15%					0.79*	0.73
					(0.46)	(0.46)
Stated probability: 16–40%					1.06	0.93
					(0.76)	(0.78)
Stated probability: 41–60%					4.91***	5.00***
					(1.61)	(1.65)
Stated probability: 61–100%					14.42***	14.70***
					(3.14)	(3.21)
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Mean of dep. var. (%)	1.98	2.01	1.98	2.01	1.98	2.01
Observations	5,744	5,519	5,744	5,519	5,744	5,519
R^2	0.041	0.046	0.047	0.052	0.046	0.051

Notes: Linear probability models with survey-wave fixed effects. The sample consists of transitions between consecutive Credit Access interviews three to five months apart, for respondents who report no refinancing application in the twelve months before the initial interview. The dependent variable equals 100 if the respondent reports an application at the next interview, which must therefore have been submitted in the intervening four months. The stated probability is the reported percent chance of applying to refinance over the next twelve months, in units of 10 percentage points. Columns (3) and (4) allow the slope to change at a stated probability of 50 percent. Columns (5) and (6) replace the linear term with indicators for ranges of the stated probability; the omitted category is a stated probability of zero. Controls are age, gender, college education, log income, credit score group, the mortgage interest rate, the loan-to-value ratio, and the debt-to-income ratio. Standard errors clustered by respondent are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

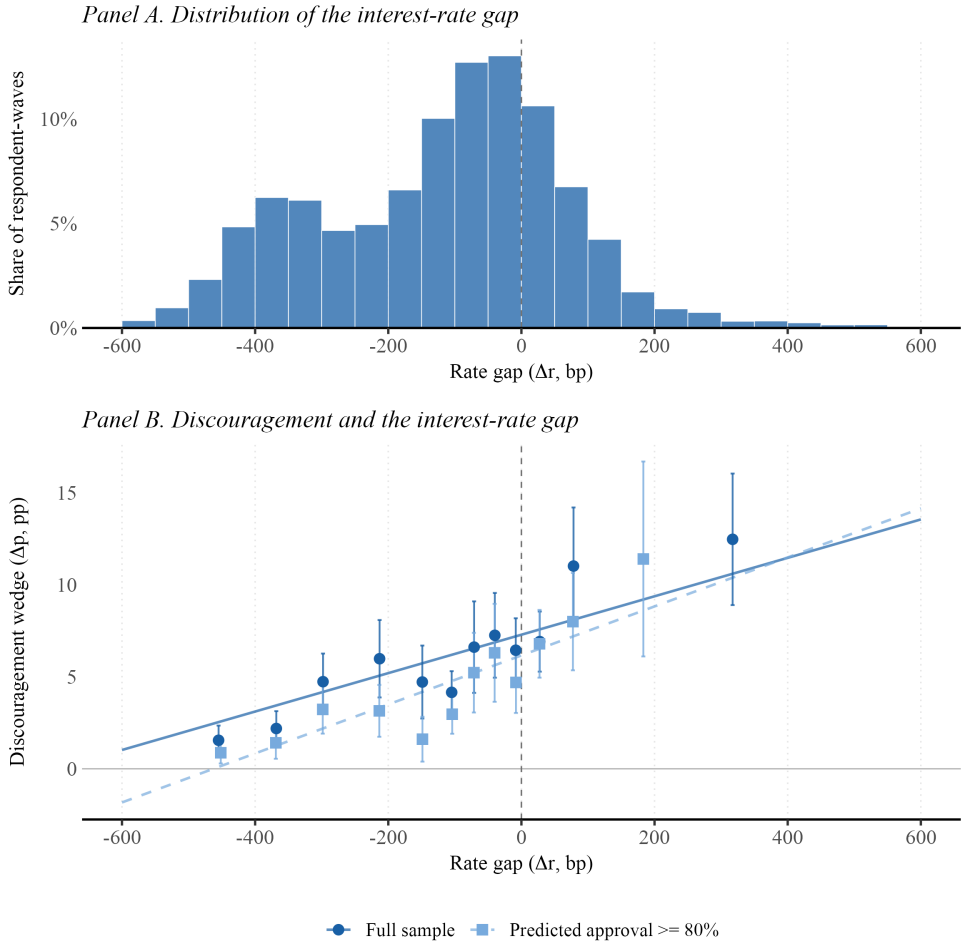
D.2 Hidden demand descriptive

Table D2: Borrower Characteristics and Discouragement

	(1) Demographics and preferences		(2) Full specification	
	Estimate	(SE)	Estimate	(SE)
Demographics and preferences				
Age 35–54	0.43	(1.60)	0.94	(1.64)
Age 55+	−3.49**	(1.67)	−0.72	(1.81)
Income $30–60k	−3.89	(3.44)	1.29	(3.46)
Income $60–100k	−4.43	(3.42)	2.58	(3.48)
Income $100k+	−9.26***	(3.37)	−0.89	(3.55)
Non-White	2.29	(1.57)	0.35	(1.52)
Male	−0.35	(1.28)	−0.23	(1.23)
College	2.72*	(1.44)	3.44**	(1.38)
Low numeracy	1.01	(1.66)	−1.70	(1.62)
Risk aversion (+1 on 1–7 scale)	0.02	(0.44)	−0.28	(0.43)
Credit score (reference: > 760)				
< 620	—	—	12.91***	(4.37)
620–679	—	—	12.33***	(2.97)
680–719	—	—	10.41***	(2.21)
720–760	—	—	4.79***	(1.42)
Mortgage and finances				
Outstanding balance (+$100,000)	—	—	1.94***	(0.51)
Mortgage rate (+1 pp)	—	—	2.24***	(0.44)
DTI 36–49%	—	—	3.44*	(1.91)
DTI 50% or more	—	—	9.50***	(2.53)
LTV (+10 pp)	—	—	0.26	(0.31)
Month fixed effects	Yes		Yes	
Observations	8,567		8,567	
R^2	0.018		0.058	
Within R^2	0.008		0.048	

Notes: Survey-weighted linear probability models with dependent variable $100 \times \mathbf{1}\{\Delta p_i > 0\}$. Coefficients and standard errors are in percentage points. Standard errors clustered by respondent are in parentheses. Both columns use the same complete-case sample; column (1) includes demographics, numeracy, and risk aversion, and column (2) adds credit and mortgage characteristics. Reference categories are age 18–34, income below $30,000, White, female, no college, high numeracy, credit score above 760, and DTI below 36%. The comparison group includes zero and negative wedges. Observations with other/unknown DTI or unknown credit score are excluded. LTV is reported per 10 percentage points, matching Figure 5. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure D1: Refinancing Incentives and Hidden Demand



Notes: Panel A shows the survey-weighted distribution of the rate gap, defined as the current mortgage rate minus the predicted refinancing rate, in 50 basis point intervals. Panel B plots the average discouragement wedge, Δp_i, against the average rate gap within common bins defined by full-sample weighted quantiles. Circles represent the full sample; squares represent borrowers with predicted approval probabilities of at least 80%. Averages use survey weights. Vertical bars show pointwise 95% confidence intervals based on standard errors clustered by respondent. Cells with fewer than 30 respondent-wave observations or 10 respondents are omitted. Lines are fitted bivariate linear regressions estimated using individual respondent-wave observations and survey weights, without controls or fixed effects. Both panels pool observations across survey waves and retain zero and negative wedges. The vertical dashed line marks a zero rate gap.

Table D3: Discouragement and the rate gap: regression estimates

Sample	(1) Full	(2) Full	(3) Strong credit	(4) Predicted approval ≥ 80%
Rate-gap groups (reference: below −100 bp)				
−100 to 0 bp	2.50***	2.55***	3.42***	3.61***
	(0.95)	(0.92)	(0.96)	(0.80)
0 to 100 bp	4.13***	4.27***	4.75***	5.75***
	(1.14)	(1.08)	(1.11)	(1.06)
Above 100 bp	8.68***	7.30***	5.99***	9.00***
	(1.79)	(1.68)	(1.44)	(1.83)
Survey-month fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	Yes	Yes
Mean of dep. var. (pp)	5.71	5.71	4.49	4.37
Observations	8,842	8,842	6,766	6,694
R^2	0.035	0.072	0.065	0.071

Notes: Survey-weighted regressions of the discouragement wedge Δp_{it} (percentage points) on the borrower-specific rate gap. It uses indicators for the rate-gap groups in Figure 4. Strong credit: credit score of at least 680 and loan-to-value ratio below 80 percent. Borrower controls are credit score group, loan-to-value ratio, log loan amount, debt-to-income group, race, sex, age, income, education, and employment status. Each sample includes respondent-waves with all controls observed. Standard errors clustered by respondent are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.3 Lost Pass-through

Table D4: Approval beliefs and predicted approval, by discouragement

	Not discouraged ($\Delta p_i \leq 0$) (1)	Discouraged ($\Delta p_i > 0$) (2)	Pooled (3)
Predicted approval (per 10 pp)	4.83***	4.57***	4.83***
	(0.52)	(0.57)	(0.52)
Discouraged (=1 if $\Delta p_i > 0$)			−10.1***
			(1.52)
Predicted approval × discouraged			−0.26
			(0.75)
Constant (belief at $\widehat{q}_i = 80\%$)	81.0***	70.9***	81.0***
	(0.93)	(1.29)	(0.93)
Observations	1,841	1,198	3,039
R^2	0.116	0.148	0.169

Notes: Weighted OLS. The dependent variable is the subjective approval probability q_i^{subj} (0–100). Predicted approval enters as $(\widehat{q}_i - 80)/10$, so its coefficient is the change in the belief, in percentage points, for a 10 pp rise in predicted approval, and the constant is the belief at $\widehat{q}_i = 80\%$. Columns (1) and (2) are estimated separately by group. Column (3) pools both groups: the discouraged coefficient is the belief gap at $\widehat{q}_i = 80\%$, and the interaction is the difference in slopes. The sample is respondents who report an approval belief and have predicted approval and Δp_i observed; respondents with $\Delta p_i < 0$ are kept. Standard errors clustered by respondent in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

D.4 Calibration counterfactual

This appendix quantifies the additional discouragement associated with beliefs below the benchmark. The exercise asks how the aggregate wedge would differ if each below-benchmark group held back the same share of its guaranteed intentions as the near-benchmark group. Group sizes and guaranteed intentions are held fixed, and the near- and above-benchmark groups retain their observed wedges.

We first consider respondents with predicted approval $\widehat{q}_i \geq 0.80$. Let g index the belief groups in Appendix Table D5, n_g denote the sum of survey weights over respondent-wave observations in group g, and $\overline{\Delta p}_g$ and $\overline{p}_g^G$ denote the corresponding weighted group means. The reference group, g_0, contains respondents whose beliefs are within five percentage points of the benchmark. Its

suppression rate is

$$s_0 = \frac{\overline{\Delta p}_{g_0}}{\overline{p}^{G}_{g_0}} \simeq 0.232,$$

or 23.2 percent. Calculations use the unrounded reference rate.

Let $\mathcal{G}_-$ contain the four groups whose beliefs are more than five percentage points below the benchmark. Their standardized wedges are $s_0\,\overline{p}^{G}_{g}$, while all other groups retain their observed wedges:

$$\overline{\Delta p}^{\,\mathrm{cf}}_{g} = \begin{cases} s_0\,\overline{p}^{G}_{g}, & g \in \mathcal{G}_-, \\ \overline{\Delta p}_{g}, & g \notin \mathcal{G}_-. \end{cases}$$

The percentage reduction in the aggregate wedge is therefore

$$R = 100\,\frac{\sum_{g\in\mathcal{G}_-} n_g \left(\overline{\Delta p}_{g} - s_0\,\overline{p}^{G}_{g}\right)}{\sum_g n_g\,\overline{\Delta p}_{g}}.$$

Panel A of Table D7 reports the results. Standardizing the below-benchmark groups lowers the average wedge from 9.0 to 6.1 percentage points, reducing the aggregate wedge by 32.4 percent, as reported in Section 6.2. The group 5–15 percentage points below the benchmark contributes a reduction equal to 4.3 percent of the original aggregate wedge; the three groups further below contribute the remaining 28.1 percent. Respondents reporting certain approval are included in the near- or above-benchmark groups according to their actual belief gap and retain their observed wedges.

Panel B repeats the exercise for all respondents reporting an approval belief. In this sample, the near-benchmark suppression rate is 27.7 percent. Standardization lowers the average wedge from 11.6 to 8.9 percentage points, a reduction of 22.8 percent.

These calculations provide a descriptive measure of excess suppression among respondents with below-benchmark beliefs. Interpreting them as the effect of correcting pessimistic beliefs requires the near-benchmark group to provide an appropriate counterfactual at similar predicted risk, including comparability in application costs and refinancing values. The exercise also treats the benchmark as an adequate measure of approval prospects. It does not estimate the effect of bringing all respondents' beliefs to the benchmark, and it does not propagate sampling uncertainty in the group means or reference rate.

Table D5: Discouragement across approval beliefs among approvable borrowers

				Intentions			Suppression
Belief relative to benchmark	Share	q_i^{subj}	$\widehat{q}_i$	p_i^{subj}	p_i^G	Δp_i	rate
More than 5 pp above	41.5	99.5	90.1	22.5	25.7	3.2	12.5
Within 5 pp	27.1	95.9	93.9	21.1	27.4	6.4	23.2
5–15 pp below	8.4	81.8	91.5	28.0	42.5	14.5	34.1
15–30 pp below	5.7	72.9	93.0	24.7	40.8	16.2	39.6
30–50 pp below	8.0	51.0	90.6	26.7	51.0	24.3	47.6
More than 50 pp below	9.3	11.9	90.2	12.3	32.1	19.8	61.5
Observations							2,266
Respondents							1,456

Notes: The sample consists of belief reporters with $\widehat{q}_i \geq 0.80$. Probabilities, group shares and suppression rates are in percent; wedges are in percentage points. Means and group shares use survey weights. Groups use $q_i^{\text{subj}} - \widehat{q}_i$; "within 5 pp includes both −5 and +5. Below-benchmark intervals include their larger shortfall endpoint. Respondents reporting certain approval are assigned according to their actual gap. The suppression rate is $100\,\overline{\Delta p}_g / \overline{p^G}_g$, the ratio of weighted group means. Observation counts are respondent-wave counts; respondent counts are unique within each sample. Differences between rounded intentions may differ slightly from the reported wedge.

Table D6: Discouragement across approval beliefs in the full belief-reporting sample

				Intentions			Suppression
Belief relative to benchmark	Share	q_i^{subj}	$\widehat{q}_i$	p_i^{subj}	p_i^G	Δp_i	rate
More than 5 pp above	46.5	92.7	73.7	24.7	32.2	7.5	23.4
Within 5 pp	21.9	89.6	87.9	22.1	30.5	8.4	27.7
5–15 pp below	8.5	67.1	76.6	23.6	41.6	18.0	43.2
15–30 pp below	7.1	58.6	79.9	24.9	41.6	16.7	40.1
30–50 pp below	7.2	44.3	83.9	24.8	49.0	24.2	49.3
More than 50 pp below	8.8	10.7	84.9	13.1	33.1	20.0	60.4
Observations							3,039
Respondents							1,880

Notes: The sample includes all respondents reporting an approval belief in the rate-linked analysis sample. Probabilities, group shares and suppression rates are in percent; wedges are in percentage points. Means and group shares use survey weights. Groups use $q_i^{\text{subj}} - \widehat{q}_i$; "within 5 pp includes both −5 and +5. Below-benchmark intervals include their larger shortfall endpoint. Respondents reporting certain approval are assigned according to their actual gap. The suppression rate is $100\,\overline{\Delta p}_g / \overline{p^G}_g$, the ratio of weighted group means. Observation counts are respondent-wave counts; respondent counts are unique within each sample. Differences between rounded intentions may differ slightly from the reported wedge.

Table D7: Suppression standardized to the near-benchmark rate

		Mean wedge (pp)		Reduction in
Belief relative to benchmark	Share (%)	Observed	Standardized	aggregate wedge (%)
Panel A. Predicted approval $\widehat{q}_i \geq 0.80$				
Reference suppression rate: 23.2%				
5–15 pp below	8.4	14.5	9.9	4.3
15–30 pp below	5.7	16.2	9.5	4.3
30–50 pp below	8.0	24.3	11.9	11.0
More than 50 pp below	9.3	19.8	7.5	12.8
Entire sample	100.0	9.0	6.1	32.4
Panel B. All respondents reporting a belief				
Reference suppression rate: 27.7%				
5–15 pp below	8.5	18.0	11.5	4.7
15–30 pp below	7.1	16.7	11.5	3.2
30–50 pp below	7.2	24.2	13.6	6.6
More than 50 pp below	8.8	20.0	9.2	8.3
Entire sample	100.0	11.6	8.9	22.8

Notes: All entries are in percent or percentage points, as appropriate. For each sample, the reference rate s_0 is the unrounded suppression rate among respondents within ±5 pp of the benchmark, expressed as a fraction. For below-benchmark group g, the standardized mean wedge is $s_0\overline{p^G}_g$. Group sizes and guaranteed intentions are held fixed; the above- and near-benchmark groups retain their observed wedges. Each group's reduction is expressed as a percentage of the entire sample's observed aggregate wedge. The entire-sample row reports observed and counterfactual weighted mean wedges and their percentage reduction. Only below-benchmark groups are listed separately. This descriptive standardization holds the composition of each group fixed; interpretation as a belief-correction counterfactual requires comparability in application costs and refinancing values at similar predicted risk.