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Chasing Lower Rates: How Households Balance Refinancing Incentives and Debt Constraints

Jiří Gregor and Jan Janků *

Abstract

This paper examines the determinants of early mortgage refinancing in a market dominated by fixed-rate loans with comparatively short reset periods. Drawing on a matched loan-level dataset covering 2015–2024, we estimate panel logit and Cox proportional hazards models to assess how borrower characteristics, market conditions, and macroprudential constraints jointly shape refinancing behaviour. The results show that households react strongly to the spread between their contractual mortgage rate and prevailing market rates, as well as to signals of future rate increases, highlighting the refinancing channel as an important conduit for the transmission of monetary policy even in fixed-rate environments. We further document that borrower indebtedness—captured by LTI, LSTI, and LTV—affects refinancing in a nonlinear manner. Moderate levels of these indicators enhance sensitivity to interest-rate incentives and facilitate refinancing, whereas very elevated values limit the borrower's opportunity or capacity to refinance.

JEL Codes: E52, G21, D14, C41.
Keywords: Hazard models, household finance, indebtedness, refinancing.

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1. Introduction

In this paper, we study the drivers of early refinancing decisions to shed light on both the effectiveness of monetary policy under fixed mortgage regimes and the potential vulnerabilities arising from large-scale rate resets. By highlighting the roles of interest rate differentials, borrower expectations, and macroprudential considerations, we offer insights into how even a nominally fixed rate mortgage market can remain sensitive to policy rates, and why policymakers must monitor the timing and distribution of mortgage refinancings in safeguarding financial stability.

Monetary policy often affects households through changes in mortgage borrowing costs. However, in a market dominated by fixed-rate mortgages, immediate pass-through is typically muted because households remain locked into a contractual rate. Yet, in the Czech Republic, legislative changes have significantly reduced the penalty for early mortgage repayment, enabling borrowers to refinance even during an ongoing fixation period. These lower refinancing barriers have re-opened a channel for monetary policy: when market rates differ sufficiently from existing contract rates, or when households expect future rate hikes, many may refinance early, causing de facto rate adjustments that can align household financing costs more closely with monetary policy signals.

This paper investigates the conditions under which Czech households choose to refinance fixed-rate mortgages before the official end of their fixation period. We pay particular attention to the role of interest rate differentials: How large a gap between a borrower's existing mortgage rate and the current market rate must be to trigger interest in refinancing, and to what extent households react to *expected* future rate changes. Our analysis leverages institutional reforms introduced by Act No. 257/2016 Coll., which transposed Directive 2014/17/EU into Czech law. By capping the fees banks can charge for early repayment at only "directly and reasonably incurred costs," the legislation has effectively lowered refinancing costs to near zero.[1] The result is that, despite having fixed-rate contracts, a substantial portion of Czech households can and do refinance when market rates fall below their locked-in rates, or if they anticipate a rise in borrowing costs.[2]

Although this refinancing mechanism strengthens monetary policy transmission, it also carries implications for macroprudential policy and financial stability. When a large number of households refinance in a low-interest rate environment, the fixed-rate terms of their loan contracts tend to mature concurrently. If interest rates have increased by then, this simultaneity may give rise to synchronized repayment shocks. Such a cycle may be seen in the Czech context: a large volume of mortgages refinanced at historically low rates in 2020–2021 will inevitably converge to the same end date several years later.[3] Consequently, when these loans are reset, a concentrated wave of households could face higher monthly payments in tandem, increasing the risk of default among

[1] Based on an opinion of the Czech National Bank (CNB) published in 2019, reasonably incurred costs may be understood as costs directly related to the act of repayment itself (administrative costs), but not lost profit (interest) or previously paid commissions (for details see CNB opinion on the interpretation of the Consumer Credit Act).

[2] A new amendment to Act No. 257/2016 Coll., effective from September 1, 2024, introduces a revised legal framework for determining early repayment fees for certain consumer housing loans. While this change expands the permissible cost recovery for lenders, it applies only to fixation periods starting after that date and thus does not affect the loans analyzed in this paper. Even under the new framework, however, the fees remain capped at levels considered minor, preserving low refinancing barriers for most borrowers.

[3] In 2021, the macro-financial and macroprudential environment in the Czech Republic was exceptionally favorable for mortgage lending, prompting banks to originate and refinance a record number of loans—many with a 5-year fixation. Thus, a substantial portion will end their fixation in 2026, potentially refixing up to CZK 350 billion (about 20% of the mortgage portfolio). Figure A1 illustrates the timeline of fixation expiration (x-axis), volume (y-axis) and year of origination (color scale), distinguishing between new (panel A) and refinanced loans (panel B). Since reference rates were below 1% and DTI/DSTI limits were suspended during 2020–2021, those contracts

particularly leveraged or lower-income borrowers. From a financial stability perspective, the alignment of fixation cycles amplifies the impact of interest rate fluctuations, underscoring the importance of understanding how and when households choose to refinance.

However, to add nuance to the threat of fixation cycles, if households are sufficiently forward-looking, many may refinance again when they foresee less favorable conditions, potentially smoothing the large, synchronized wave of fixations. Yet, it remains an open question whether this behavior is entirely symmetrical: exiting a high-rate contract when market rates fall seems more straightforward than proactively refinancing an already low-rate contract based on uncertain predictions of future market rates or central bank actions. Whether borrowers incorporate anticipated rate changes into their refinancing decisions thus becomes a key issue. If they do, early refinancing could mitigate fixation cycle risks; if not, a sizable cohort of loans may still reset simultaneously under adverse conditions. We therefore also examine this forward-looking behavior of consumers.

Our paper shows that households respond strongly to interest rate incentives, both current and anticipated. A wider gap between the borrower's mortgage rate and the prevailing market rate, as well as higher expected future rates, significantly boost refinancing likelihood. Borrowers with larger loans are especially quick to refinance—likely reflecting greater absolute savings, while those with higher income appear less motivated to capture rate differentials. Macroprudential measures, such as loan-to-income (LTI) or loan-to-value (LTV), also play a role. Borrowers facing tighter payment burdens demonstrate higher sensitivity to rate changes, yet extremely indebted households can be hampered by stricter credit constraints. Finally, survival analysis confirms that timing matters. Those facing strong financial incentives or anticipating rising rates refinance earlier in the fixation period.

The rest of the paper is organized as follows. Section 2 discusses the determinants of mortgage refinancing, focusing on refinancing behavior in a market dominated by fixed-rate mortgages. Section 3 explains the data and matching procedures used to identify whether individual loans were refinanced or not. Section 4 presents our empirical framework, including the methodology and descriptive statistics. In Section 5, we analyze the determinants of refinancing in a logit setting, while Section 6 examines the timing of refinancing decisions. Section 7 then provides several robustness checks. Finally, Section 8 concludes with a summary of our main results and their policy implications.

2. Literature review

Mortgage refinancing represents one of the transmission channels through which monetary policy impacts household balance sheets and broader economic outcomes. Its effectiveness depends significantly on economic conditions, institutional structures, and borrowers behavior. Monetary policy pass-through via refinancing is particularly worth investigating in economies where mortgages predominantly feature fixed interest rates. Gaffney et al. (2021) highlight that increased use of fixed-rate mortgages reduces refinancing responsiveness because lenders typically charge early redemption penalties. However, in environments where penalties are minimal or waived, fixed-rate borrowers can benefit significantly from lower market rates during monetary easing, reducing monthly debt service obligations and increasing household disposable income and consumption (Agarwal et al., 2018; Di Maggio et al., 2017). Nevertheless, refinancing remains

have been protected from recent rate increases, but not indefinitely. The figure highlights how many loans will soon exit their fixation, possibly facing higher rates.

inaccessible to many households during downturns, especially for those facing negative equity or who cannot document sufficient income, thereby limiting policy effectiveness precisely when monetary relief is most needed (Beraja et al., 2019; DeFusco and Mondragon, 2020).

The literature distinguishes between two central monetary policy channels affecting mortgage refinancing: the *new credit channel*, prominent in expansions, and the *interest burden channel*, critical in downturns (Richter, 2017). The latter notably affects economies dominated by short-term fixed-rate mortgages, such as the Czech Republic, where periodic interest rate resets expose households to cyclical refinancing pressures closely aligned with monetary policy decisions (Kelly and Myers, 2019). During episodes of monetary easing, large groups of borrowers refinance simultaneously, potentially creating systemic refinancing risk when interest rates subsequently rise (Richter, 2017).

Refinancing behavior significantly influences the transmission of monetary policy through its direct impact on household liquidity and aggregate consumption. Empirical evidence from the U.S. highlights that younger homeowners, who typically hold larger mortgages and face greater liquidity constraints, exhibit stronger consumption responses following monetary policy rate cuts due to their higher propensity to refinance (Wong, 2019). Refinancing effectively reduces monthly debt service, directly alleviating short-term liquidity constraints, thereby amplifying monetary policy effectiveness (Wong, 2019; Di Maggio et al., 2020). Furthermore, Eichenbaum et al. (2022) illustrate how the refinancing channel's effectiveness crucially depends on the distribution of household equity, showing that a prolonged low-interest-rate environment can blunt future monetary policy potency by reducing refinancing incentives. Similarly, Beraja et al. (2019) demonstrate that the geographic distribution of housing equity significantly influences the aggregate impact of monetary easing, with depressed regions showing weaker refinancing responsiveness, thus dampening the overall transmission of monetary policy.

Cross-country studies corroborate the significance of refinancing and cash-flow channels. For instance, Di Maggio et al. (2017) find robust evidence of the cash-flow channel in the U.S., where lower repayments from adjustable-rate mortgages substantially boost household consumption. Comparable evidence emerges internationally: La Cava et al. (2016) document similar findings in Australia, Jappelli and Scognamiglio (2018) in Italy, and Floden et al. (2021) in Sweden, underscoring that households with adjustable-rate mortgages consistently increase consumption following monetary easing due to immediate cash-flow improvements. Theoretically, Garriga et al. (2017) clarify that the consumption response under adjustable-rate mortgages tends to be only modestly stronger than fixed-rate mortgages if monetary shocks are temporary. However, they emphasize that this gap becomes notably larger under persistent monetary shocks, aligning with empirical findings by Di Maggio et al. (2017). Behavioral frictions further complicate refinancing patterns; Berger et al. (2025) highlight borrower inattention as a critical factor, showing that inattentive households refinance suboptimally—either too early or too late—which significantly impedes the intended transmission of monetary easing.

The literature specifically addressing fixed-rate mortgages emphasizes that borrowers should optimally refinance whenever the present value of future interest savings compensates for refinancing costs, including the time value of the refinancing option (Bennett et al., 2001; Agarwal et al., 2013). However, empirical evidence consistently demonstrates deviations from these optimal refinancing rules. Borrowers frequently refinance when it is suboptimal (Chang and Yavas, 2009), or conversely, fail to refinance even when substantial savings are achievable (Giliberto and Thibodeau, 1989). For instance, Green and LaCour-Little (1999) document widespread borrower inertia, illustrating that many fixed-rate mortgage holders remain passive despite clear incentives to refinance. Similarly, Agarwal et al. (2016) identify systematic refinancing errors driven by borrower misconceptions or miscalculations. Additionally, a study of fixed-rate borrowers in Italy (Bajo and Barbi, 2018) highlights that despite substantial reforms abolishing prepayment penalties and simplifying refinancing procedures, only 13% of eligible borrowers refinanced.

Empirical research consistently demonstrates that refinancing decisions deviate significantly from rational economic predictions, with borrowers frequently refinancing too late or not at all (Keys et al., 2016; Agarwal et al., 2017). Interest rate fluctuations strongly influence refinancing behavior. Historically, modest rate declines in the US during the late 1990s and early 2000s prompted refinancing booms as borrowers sought to lock in lower rates (Bennett et al., 1999). More recently, historically low rates (around 3%) during 2020–2021 led to unprecedented refinancing volumes, whereas the sharp rate rise in 2022 virtually halted refinancing activity, illustrating a pronounced "lock-in" effect (Zhou, 2022).

Beyond interest rates, refinancing decisions depend significantly on home equity or LTV ratios. High LTV ratios or negative equity could restrict refinancing access, particularly during economic downturns. For example, during the Great Recession, approximately one-quarter of U.S. mortgage borrowers faced negative equity, and many others had insufficient equity to qualify under typical lender standards (Agarwal et al., 2023). Borrowers' creditworthiness also critically shape refinancing eligibility. Borrowers with poor credit, unstable income, or elevated debt burdens frequently face refinancing denial or prohibitive terms, excluding financially vulnerable households precisely when refinancing could be most beneficial (DeFusco and Mondragon, 2020). Evidence from the Great Recession highlights that stricter DTI and underwriting standards considerably curtailed refinancing among financially constrained households (DeFusco and Mondragon, 2020).

Behavioral and psychological factors additionally influence refinancing dynamics. Research identifies substantial refinancing inertia arising from risk aversion, procrastination, financial illiteracy, and complexity aversion (Agarwal et al., 2017; Johnson et al., 2019). Bajo and Barbi (2018) finds that financial literacy significantly influences refinancing behavior, with less-educated, lower-income, immigrant, female, and southern households notably less likely to refinance, whereas borrowers with backgrounds in finance or economics exhibit higher refinancing propensity. Also, borrowers skeptical of financial institutions often abstain from refinancing due to distrust, even in favorable conditions (Johnson et al., 2019). Behavioral economics highlights how cognitive biases like present bias and inattention lead to widespread refinancing delays, as households disproportionately weigh immediate costs of refinancing (such as fees and paperwork) over future benefits (Andersen et al., 2015; Campbell et al., 2011). Notably, financial literacy strongly influences refinancing uptake, with financially sophisticated borrowers recognizing and acting promptly on refinancing opportunities (Campbell, 2006; Agarwal et al., 2017). Indeed, experimental interventions, such as personalized reminders, have effectively reduced inertia, underscoring how simple nudges can counteract behavioral frictions (Johnson et al., 2019).

Theoretical frameworks often conceptualize refinancing decisions through option-based models, likening refinancing to exercising a financial call option. Such models typically identify refinancing as optimal when market rates fall between 100–200 basis points below the original mortgage rate (Agarwal et al., 2013). However, empirical refinancing behavior substantially diverges from these theoretical optima, driven by previously discussed psychological factors, information asymmetry, and market frictions (Keys et al., 2016; Agarwal et al., 2016). Recent theoretical advances integrate these frictions explicitly, better aligning models with observed refinancing patterns, including cases of significant borrower inertia even in highly favorable conditions (Agarwal et al., 2017; Johnson et al., 2019).

Finally, macroeconomic conditions play a critical role in shaping refinancing trends. Refinancing volume historically correlates closely with economic expansions characterized by rising home values, low unemployment, and declining interest rates (Freddie Mac, 2022). Conversely, recessions yield mixed refinancing outcomes, as lower rates may stimulate demand but are often offset by negative equity, job losses, and tightened credit standards, restricting refinancing access (DeFusco and Mondragon, 2020). Recent refinancing cycles demonstrate pronounced volatility, highlighting significant racial and income-based refinancing disparities during economic booms, indicating persistent access and informational inequalities despite broad economic incentives (Freddie Mac, 2021). Thus, a comprehensive understanding of mortgage refinancing behavior requires consideration of economic fundamentals, institutional structures, macroeconomic conditions, and nuanced behavioral insights, collectively shaping the effectiveness of monetary policy through mortgage markets.

3. Data and Hypotheses

The primary data source is the Survey of Newly Granted Loans Secured by Residential Property (hereafter referred to as the Survey), which the CNB conducts quarterly.[4] The dataset includes information on all new mortgage contracts, namely new loans, loans with increased principal, and loans refinanced with a different bank than the original one. However, the Survey does not contain loans where the rate was re-fixed at the original bank without an increase in principal. The dataset includes approximately 1 million loans granted between July 2015 and May 2024. Mortgages originated before 2015 and not refinanced to date (i.e., with fixation periods longer than eight years) are omitted from the sample. In 2014, such loans accounted for only 2–3% of all new loans, so their current volume is negligible.

For each mortgage loan at the client level, the data provide variables such as signing date, maturity date, end of fixation period, client age, and client income. Figure 1 and Figure A1 in Appendix show that five-year fixations were the most common among new mortgage contracts (nearly 50% of all new loans between July 2015 and May 2024). However, with the rise in interest rates after 2021, the share of mortgages with a five-year or longer fixation has fallen sharply.

Since our analysis centers on the incentives for consumers to refinance, we need to match new and refinanced loans. Figure 2 indicates that households refinanced more frequently during low-rate periods (2016–2017 and 2020–2021) and less often when rates were higher (2018–2019 and especially 2022–2024).[5] However, the data lack a unique identifier (client or loan ID) to directly link new loans with refinanced loans, a limitation that dictates our analytical approach.

3.1 Matching Procedure

Before matching, we clean the data of apparent errors and deficiencies and remove bridge loans from building societies, loans with non-standard repayment schedules, and loans missing essential characteristics. We then restrict our sample to new loans originated between January 1, 2016, and

[4] The data structure has undergone multiple changes since 2015, and the scope of collected information has gradually expanded.

[5] Refinancing means that households terminate their contract with the current bank and move to a new contract at another bank.

Figure 1: Number of New Mortgage Loans by Fixation Periods

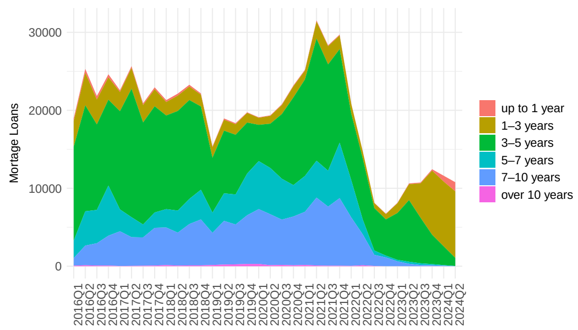
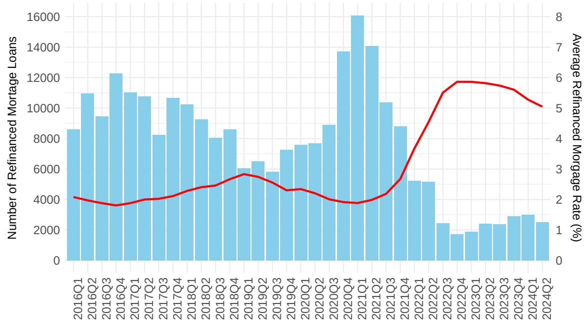


Figure 2: Number of Refinanced Mortgage Loans and Average Mortgage Rate



Note: Figure 1 depicts the quarterly count of new mortgage loans split by fixation length. A large share typically goes to five-year fixations, though the mix changes over time. Figure 2 displays quarterly refinancing numbers (bars) and the average mortgage rate (red line). Refinancing surges when rates are low and wanes as they rise. Data for Q2 2024 include data for April and May only.

December 31, 2018, with a fixation period of 3 to 5 years. Mortgages with longer fixations may extend beyond Q2 2024 (the limit of our dataset), making them unsuitable for reliable matching. This yields 138,517 new mortgage loans. We do not include loans originated in later years (e.g. 2019 or 2020), as the maximum admissible fixation length would be mechanically shorter for these vintages, implying a different sample selection rule and uneven exposure to refinancing risk across cohorts. Restricting the sample to the 2016–2018 vintages ensures a uniform observation window and consistent refinancing eligibility across all loans.

Our matching process proceeds in four steps. **In the first step**, we form a pseudo-ID by combining the property's ZIP code, the number of applicants, and a dummy variable indicating the loan's purpose (rental vs. other). We then link each new loan with potential refinanced loans that share the same pseudo-ID. Because this initial approach is too coarse, we next, **in the second step**, impose more restrictive conditions, including: (i) the refinanced loan's origination date must be strictly later than that of the new loan, (ii) the change in the applicant's age must match the elapsed time between origination and refinancing, (iii) the refinanced loan must be issued by a different bank, and (iv) there must be a minimum 3-month gap between the original loan origination and the refinancing.[6]

In the third step, we define additional conditions that are very likely to be valid, but not exclusively. We refine the matching further by requiring that (i) the collateral value of the refinanced loan is at least that of the new loan, taking into account rising real estate prices between 2016 and 2023, (ii) the maturity date of the refinanced loan cannot exceed the original loan's maturity by more than 180 days,[7] (iii) the refinancing date precedes or coincides with the fixation end date of the new loan, and (iv) the refinanced loan amount cannot exceed that of the new loan unless the principal was explicitly increased.

Finally, **in the fourth** and last step, we select the final dataset so that it contains only uniquely matched loans. For loans with multiple matches, only the first match is retained. After applying all these steps, we identify 18,328 new loans that successfully match with a refinanced loan, and

[6] We apply this threshold to ensure that the original mortgage was active long enough to represent a genuine financing arrangement, and to avoid incorrect matches caused by data-reporting issues.
[7] Following the CNB's recommendation to avoid maturity extensions for refinanced loans.

48,785 new loans for which no matching refinanced loan is found by the second step. The remaining 71,404 loans show ambiguous or conflicting information and are excluded from our sample. We then combine the matched, refinanced loans and the non-refinanced loans into a single dataset for estimation.

We strictly define refinanced loans after completing the third step to ensure that all refinement criteria are met, such as collateral values, maturity dates, and correct timing. This approach minimizes false positives and thus enhances the accuracy of our classification. By contrast, any loan that remains unmatched following the second step (before we apply the additional filters) is deemed non-refinanced, reflecting the conservative choice that no plausible candidate for a refinanced loan could be found. We opted for this conservative design to avoid overestimating refinancing rates based on partial matches or coincidental similarities in the data. The result is a dataset that distinguishes confidently identified refinanced loans from both unambiguously non-refinanced loans and those with inconclusive or conflicting information.

However, as a robustness check, we refine the identification of refinanced loans by incorporating the structure of the repayment schedule into the matching criteria. Specifically, we determine the minimum possible loan amount that could have been refinanced given the repayment schedule.[8] A loan is classified as refinanced only if the refinanced principal exceeds this implied minimum. At the same time, we relax the identification of non-refinanced loans and classify all loans unmatched after the third matching round as non-refinanced. This approach is intentionally much less conservative, in the treatment of non-refinanced loans, than our baseline and is used solely for robustness, not as our preferred identification strategy. The resulting dataset contains 10,606 refinanced loans, 123,351 non-refinanced loans, and 4,560 ambiguous loans.

We posit that two main factors drive refinancing: the spread between the current rate and the rate at origination, and the gap between the current rate and the anticipated rate at the end of the fixation period. Figures 3 and 4 indicate that most refinancing took place in 2017–2018 and again in mid-2020 through 2021. During the first interval, refinancing appears largely driven by the interest-rate outlook, whereas in the second interval, both the outlook and the rate differential play key roles. After 2021, as mortgage rates rose sharply, the appetite for refinancing declined, with most households opting to wait until their fixation period concluded.

[8] Since our sample includes only loans with a maximum fixation period of up to five years, we assume that the smallest possible outstanding principal corresponds to the remaining balance after 72 monthly installments under annuity repayment.

Figure 3: Number of Refinanced Loans and Mortgage Rate Differential

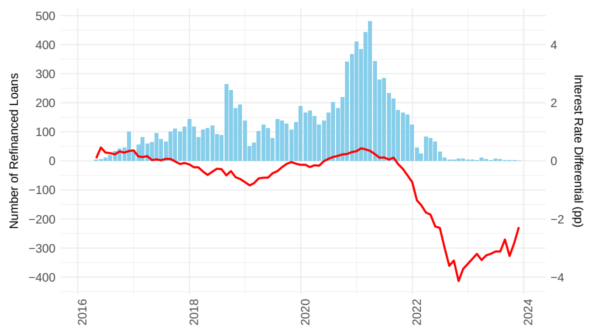
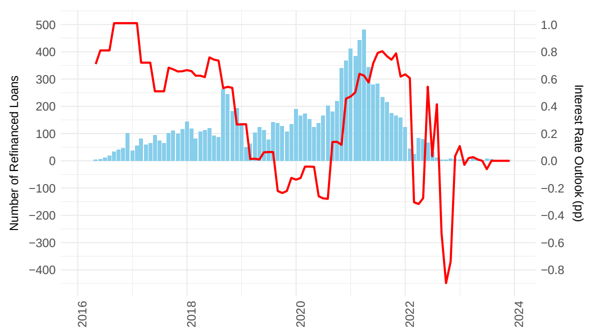


Figure 4: Number of Refinanced Loans and Interest Rate Outlook



Note: Blue bars shows the number of refinanced loans in the matched dataset in a given month. Red line in the left panel (Figure 3) demonstrates the mortgage rate differential defined as the difference between the borrower's original/contractual mortgage rate and the prevailing market rate at the time of refinancing. Red line in the right panel (Figure 4) shows the interest rate outlook measured as the expected change in short-term market rates over the next nine months (based on PRIBOR forecasts). A positive outlook suggests borrowers anticipate rising rates.

3.2 Hypotheses

In line with the existing literature on refinancing behavior, we expect that both individual borrower characteristics and market conditions (interest-rate incentives and macroprudential constraints) significantly influence the likelihood of refinancing.

First, we hypothesize that a larger mortgage rate differential (`MoRD`)—the gap between a borrower's contract rate and the prevailing market rate—will increase the likelihood of refinancing. This intuition follows from the economic rationale that when the contract rate substantially exceeds current market rates, the potential savings from switching loans grows large enough to outweigh refinancing costs (Agarwal et al., 2013; Keys et al., 2016).

Second, we hypothesize that stronger expectations of future rate increases (`expR`) similarly raise the probability of refinancing. When borrowers anticipate rising interest rates, they may attempt to lock in a currently lower rate, thus preempting future payment shocks. This forward-looking behavior is consistent with evidence that households incorporate expected monetary policy conditions into their refinancing decisions (Campbell and Cocco, 2003; Di Maggio et al., 2017).

Third, we hypothesize that higher macroprudential indicators, such as `LSTI`, `LTI`, or `LTV`, will be associated with an elevated propensity to refinance, albeit in potentially non-linear ways. On the one hand, more leveraged borrowers face stronger incentives to reduce their monthly outlays by refinancing; on the other, excessive indebtedness can limit their ability to qualify for new loans or benefit from favorable terms (Campbell and Cocco, 2015; Agarwal et al., 2016). Consequently, while moderate leverage may facilitate refinancing, extremely high levels of debt or low equity can diminish a borrower's refinancing prospects, particularly when stricter lending standards come into play.

4. Methodology

The dependent variable is a binary indicator representing the refinancing decision, coded as 1 if the loan was refinanced and 0 otherwise. Key independent variables include the mortgage rate differential (`MoRD`), defined as the difference between the borrower's current mortgage rate and the average prevailing market mortgage loan rate in a given month, and the expected change in interest rates, `expR`, which represents the projected change in the PRIBOR rate over a 6- to 12-month horizon (our baseline is 9 months, but we test all alternatives in the robustness checks). Specifically, it is calculated as the predicted difference between PRIBOR at $t+x$ months and the current PRIBOR rate.

Additional covariates include macroprudential indicators (vector $\texttt{MacPru}_{it}$), such as the loan-service-to-income ratio (`LSTI`), which measures the borrower's monthly debt service relative to monthly income and captures the affordability of the loan. Alternatively, the model includes the loan-to-income (`LTI`) ratio, which represents the total loan amount relative to the borrower's annual income, and the loan-to-value (`LTV`) ratio, which reflects the amount of the loan in relation to the borrower's equity.

Other borrower-level controls include age at origination (`Age_Client`) and its square (`Age_Client^2`) to account for potential non-linear life-cycle effects. Employment/self-employment status is captured via a binary indicator `Employee_Yes`. We also control for whether the loan was arranged without a broker (`Broker_No`), which may proxy for financial literacy or information access. Loan-specific characteristics include the size of the mortgage `log(Loan_Size)` and borrower income, `log(Net_Income)`, both in logarithmic form to account for skewness. To address heterogeneity in refinancing behavior, we further include fixed effects for borrower region (`Region`), originating bank (`Bank`), and the year of fixation start (`Year`). Together, these controls help isolate the role of interest-rate incentives and borrower constraints in driving refinancing decisions.

4.1 Panel Logit Regression

First, we employ a panel logit model by converting our data into a standard panel structure. This approach generates monthly observations for each household over the fixation period of their mortgage loan, allowing us to examine why households decided to refinance (dependent variable `Refinanced` coded as 1 in the month of refinancing) or not (coded as 0). If a household did not refinance during the fixation period, all observations for the dependent variable remain zero. If refinancing occurred, the dependent variable equals 1 at the time of refinancing, and the household exits the sample thereafter, as its post-refinancing characteristics would no longer be comparable to the original loan spell.

To account for variation over time, across banks, and between regions, we include fixed effects for years (`Year`), the originating bank (`Bank`), and the borrower's region (`Region`). Year fixed effects absorb all aggregate macro-financial conditions, such as monetary policy shifts, business-cycle dynamics, or regulatory changes, ensuring that our estimates are robust to common shocks. Bank and region fixed effects control for supply-side differences and local housing-market conditions, preventing these factors from confounding the estimated refinancing determinants.

The panel logit model is represented by the following equation:

$$\log\left(\frac{P_{it}}{1-P_{it}}\right) = \beta_1\, MoRD_{it} + \beta_2\, expR_{it} + \beta_3\, MacPru_i + \beta_4 X_i + \lambda_t + \mu_j + \rho_r + \varepsilon_{it} \tag{1}$$

where P_{it} denotes the probability that household i refinances at time t; λ_t captures year fixed effects (`Year`); μ_j are fixed effects for the originating bank (`Bank`); and ρ_r are region fixed effects (`Region`). The variable $\texttt{MoRD}_{it}$ denotes the mortgage rate differential, and $\texttt{expR}_{it}$ captures expected future interest rate changes in 9 months. The vector $\texttt{MacPru}_i$ includes time-invariant macroprudential indicators such as `LSTI`, `LTI`, and `LTV`, while $\texttt{X}_i$ includes borrower characteristics like `Age_Client`, `Net_Income`, `Loan_Size`, `Broker_No`, and `Employee_Yes`. Standard errors are clustered at the loan level. The variables are described in detail in Table A3.

The vector $\texttt{MacPru}_i$, which includes macroprudential controls such as the loan-to-income (LTI), loan service-to-income (LSTI), and loan-to-value (LTV) ratios, along with other control variables X_i, is time invariant for each loan. These characteristics were established at the time the loan was granted and remain constant throughout the fixation period due to data limitations.

4.2 Cox Proportional Hazards Model

Second, to analyze the timing of refinancing decisions among borrowers, we employ the Cox proportional hazards model, a semi-parametric approach designed to examine time-to-event data. In our case, we use a panelized (start–stop) design, where each mortgage loan contributes multiple monthly observations until either refinancing occurs (event) or the fixation period ends (censored). This structure allows us to capture the evolving influence of time-varying covariates, such as market interest rate conditions, on refinancing behavior.

The Cox proportional hazards model is expressed as:

$$h(t|X_{it}) = h_0(t)\exp\left(\beta_1\, MoRD_{it} + \beta_2\, expR_{it} + \beta_3\, MacPru_i + \beta_4 X_i + \lambda_t + \mu_j + \rho_r\right) \tag{2}$$

where $h(t|X_{it})$ denotes the hazard rate—i.e., the instantaneous likelihood of refinancing at time t—for mortgage i, given both time-varying ($\texttt{MoRD}_{it}, \texttt{expR}_{it}$) and time-invariant covariates ($\texttt{MacPru}_i, X_i$). The term $h_0(t)$ is the baseline hazard function, common to all loans, while λ_t, μ_j, and ρ_r capture year, region, and bank fixed effects, respectively. [9]

4.3 Descriptive Statistics

Table A2 displays summary statistics for new mortgage loans, with separate columns for loans that were ultimately refinanced and those that were not. We report standard descriptive measures for key numerical variables and also identify the most common category (modus) for select categorical variables.

Both the mortgage rate differential (`MoRD`) and the expected rate change (`expR`) show notable differences at the time of refinancing or refixing—that is, when borrowers either switch lenders or

[9] The Cox model assumes proportional hazards, that is, the effect of covariates on the hazard rate is multiplicative and constant over time. We validate this assumption using Schoenfeld residuals. Time-varying covariates like (`MoRD`, `expR`) are updated monthly within the start–stop framework, ensuring that the model captures within-loan changes in refinancing incentives.

remain with their original bank and enter a new fixation period without terminating the contract early. These differences are particularly visible in the median values. For instance, borrowers are more likely to refinance when the anticipated interest rate in 9 months exceeds the current market rate (0.29 vs. –0.15), supporting the notion that stronger incentives arise when households expect rates to rise.

Borrower-level attributes reveal that refinanced loans typically come from borrowers with lower average net incomes at origination yet larger loan amounts, possibly because such borrowers expect more substantial absolute savings from a rate reduction. The age gap between the two groups is also pronounced: refinanced borrowers are younger on average, suggesting that earlier in the mortgage lifecycle, borrowers may be more proactive about leveraging favorable market conditions. Macroprudential indicators reinforce these patterns: refinanced loans generally have higher loan-to-value (LTV) and loan service-to-income (LSTI) ratios, indicating that borrowers with heavier debt burdens tend to be more rate-sensitive and thus more motivated to refinance in response to even modest interest rate movements.

In terms of categorical variables, `Broker_No` indicates whether a borrower arranged the mortgage without a broker (i.e., directly through a bank). The data suggest that a higher share of refinanced borrowers obtained their loans via a broker, which could reflect easier access to information, more competitive rate offers, or structured follow-ups that make refinancing more attractive or straightforward. Another possibility is that broker compensation might be partly linked to new originations or refinancing deals, creating an incentive for brokers to encourage refinancing once rate differentials favor the borrower. Meanwhile, `Employee_Yes` indicates a borrower's employment status, with employed borrowers displaying a higher tendency to refinance—possibly reflecting that stable income streams facilitate refinancing approval. Lastly, statistics on bank size show that borrowers initially tend to choose medium-sized banks but often move to larger institutions when refinancing, underscoring how institutional characteristics may also shape refinancing decisions.

5. Factors Influencing Refinancing Decisions

Our logit estimates indicate that borrowers are significantly more likely to refinance when the gap between their current mortgage rate and the prevailing market rates (`MoRD`) is larger, and when they anticipate higher interest rates in 9 months (`expR`). In the simplest specification, the `MoRD` coefficient is approximately 0.057 ($p < 0.001$), which translates into a roughly 5.9% increase in the odds of refinancing for each additional percentage-point increase in the rate gap.[10] The positive sign on `expR` (around 0.21, $p < 0.001$) implies that borrowers also act in anticipation of future interest rate increases, locking in lower rates to avoid potentially higher borrowing costs later.

Borrower- and loan-level variables further illuminate these decisions. Higher-income households (with a coefficient on log(`Net_Income`) around -0.34) appear less sensitive to potential savings from refinancing, whereas borrowers with larger loans are more likely to refinance, presumably because even small rate reductions lead to substantial absolute savings. Age follows a quadratic pattern, rising until about the early 50s and then declining, which may reflect evolving risk preferences or life-cycle planning.

[10] Odds ratios are calculated as e^{β}. Hence, for $\beta = 0.057$, $e^{0.057} \approx 1.059$, indicating a 5.9% increase in the odds of refinancing for a one-unit rise in `MoRD`.

Three macroprudential indicators—`LSTI`, `LTI`, and `LTV`—provide additional insight. While the coefficients are relatively modest (`LSTI` $\approx$ 0.003, `LTI` $\approx$ 0.044, `LTV` $\approx$ 0.011), each correlates positively with refinancing. This suggests that households facing tighter constraints on monthly payments (reflected in `LSTI`) have stronger incentives to lower their borrowing costs, while those with higher `LTIs` or `LTVs` may refinance to secure more favorable terms or reduce leverage.

Because Prague represents more than 10% of all mortgage loans, we tested the robustness of our findings by excluding Prague from the sample (column 5). The main conclusions remain unchanged, underscoring the robustness and consistency of the results across different regional contexts.

Table B2 introduces bank-size indicators, instead of bank FEs, for both the original and refinancing bank, with large banks as the baseline. Borrowers originating with medium banks are less likely to refinance, while those from small banks show a greater propensity to do so. On the refinancing side, switching to a medium bank is more likely, whereas moving to a small bank is less likely. Figure B3 underscores these switching patterns in detail, revealing that small bank clients refinance mainly at medium and large banks.

Table 1: Baseline Logit Model Results

	Dependent variable:				
	Refinancing Decision (1 = Refinanced, 0 = Not)				
	(1)	(2)	(3)	(4)	(5, without Prague)
MoRD	0.057^{***}	0.033^{**}	0.055^{***}	0.032^{**}	0.052^{***}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
expR	0.213^{***}	0.210^{***}	0.212^{***}	0.214^{***}	0.236^{***}
	(0.026)	(0.026)	(0.026)	(0.026)	(0.028)
log(Net_Income)	-0.340^{***}				-0.313^{***}
	(0.017)				(0.019)
log(Loan_Size)	0.185^{***}				0.185^{***}
	(0.012)				(0.013)
LSTI		0.003^{***}			
		(0.001)			
LTI			0.044^{***}		
			(0.003)		
LTV				0.011^{***}	
				(0.0004)	
Age_Client	0.438^{***}	0.427^{***}	0.426^{***}	0.424^{***}	0.435^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Age_Client^2	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Broker_No	-0.209^{***}	-0.259^{***}	-0.239^{***}	-0.225^{***}	-0.192^{***}
	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)
Employee_Yes	1.179^{***}	1.249^{***}	1.261^{***}	1.221^{***}	1.376^{***}
	(0.029)	(0.026)	(0.027)	(0.026)	(0.031)
Constant	-11.720^{***}	-13.270^{***}	-13.460^{***}	-14.010^{***}	-12.990^{***}
	(0.260)	(0.170)	(0.170)	(0.170)	(0.290)
Region Controls	YES	YES	YES	YES	YES
Year Controls	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Observations	3,261,928	3,261,928	3,261,928	3,261,928	2,836,445
Log Likelihood	−103,917	−104,137	−104,051	−103,788	−89,579
Akaike Inf. Crit.	207,913	208,351	208,199	207,654	179,237

Note: *p<0.05; **p<0.01; ***p<0.001. Each column (1–5) shows a logit specification estimating the probability of refinancing (1 = yes, 0 = no). The main predictors are the mortgage rate differential (MoRD) and the expected rate change (expR), alongside borrower-level covariates. All columns include region, year, and bank fixed effects. Coefficients are log-odds; Standard errors (in parentheses) are clustered at the loan level.

5.1 Macroprudential Policy Indicators in Detail

Table 2 presents six logit regressions linking borrowers' refinancing decisions to `expR`, `MoRD`, and three macroprudential indicators: `LSTI`, `LTI`, and `LTV`. Each discrete bracket for `LSTI`, `LTI`, and `LTV` is interpreted relative to a baseline category, namely [0,15) for `LSTI`, [0,1.5) for `LTI`, and [0,50) for `LTV`.

Columns (1) and (2) show that as `LSTI` increases beyond the baseline bracket, the odds of refinancing consistently rise, yet this effect attenuates in the highest bracket of 30 or above. This outcome suggests that heavily indebted borrowers may be constrained by stricter credit checks or less favorable offers, which can reduce the incentive or feasibility of refinancing. In columns (3) and (4), a comparable trend emerges for `LTI`, where moderate brackets (for example, 3–5 or 5–6.5) substantially increase the odds of refinancing. However, the very highest bracket (6.5 or above) exhibits a diminished impact, again signaling that extremely indebted households face more barriers to refinancing.

By contrast, columns (5) and (6) examine `LTV` and reveal a more linear relationship. Higher brackets, such as 50–60, 60–70, 70–80, and 80+, each boost refinancing significantly relative to the [0,50) reference category. Moreover, the continuous specification for `LTV` indicates no statistically significant quadratic term, suggesting that borrowers with elevated loan-to-value ratios remain consistently inclined to refinance, potentially to mitigate escalating monthly payments or secure lower rates before their equity position deteriorates further.

We extend our analysis by interacting `MoRD` with each macroprudential indicator (`LSTI`, `LTI`, and `LTV`), incorporating squared terms to capture potential non-linearities. To implement this, we first estimate a logit model that includes both the main and interaction effects of `MoRD` and the selected macroprudential variable. We then generate predicted refinancing probabilities over a systematically constructed grid of `MoRD` and `LSTI/LTI/LTV` values while holding other covariates (such as `expR`, `Age_Client`, and fixed effects for year, region, and bank) at representative levels—typically the sample means or the most frequent categories.[11]

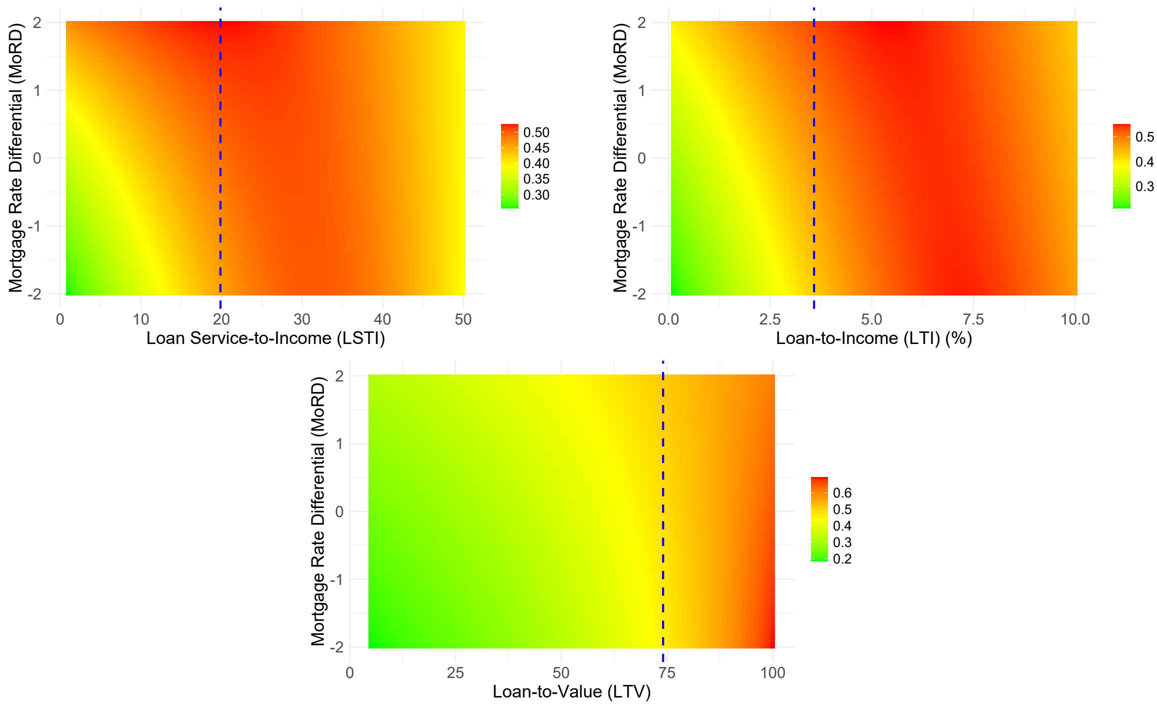
Figure 5 displays the resulting heatmaps, where the horizontal and vertical axes span the specified ranges of `MoRD` and the chosen macroprudential indicator. For instance, in the `LSTI` interaction scenario, we construct a fine grid of `MoRD` values (from -2 to 2) and `LSTI` (e.g., from a lower bound in the data up to 50). We then plot the predicted refinancing probability using a color gradient that transitions from green (low probability) to red (high probability). A dashed vertical line denotes the sample median `LSTI` to illustrate how sensitive the predicted probabilities become as `LSTI` rises above or dips below central values.

The heatmaps reveal consistent patterns across all macroprudential indicators: while very low values of `LSTI`, `LTI`, or `LTV` generate only modest responses to `MoRD`, moderate levels of these indicators amplify the effect of a widening mortgage rate differential. However, in the uppermost brackets—particularly for `LTI`—the incremental gain from further rate differentials may taper, likely due to stricter credit constraints or narrower refinancing options for heavily indebted borrowers. By contrast, `LTV` shows a more linear upward shift in refinancing probability,

[11] These predicted probabilities are computed by transforming the linear predictor from our logit model via $\widehat{p} = \frac{1}{1+\exp\left(-(\hat{\beta}X)\right)}$, where $\hat{\beta}X$ denotes the linear predictor from the logit model, so that each grid point yields a unique predicted likelihood of refinancing.

suggesting that even when we account for interactive terms, higher leverage is associated with steadily greater sensitivity to interest-rate reductions.[12] [13]

Figure 5: Probability of Refinancing - Interaction of MacPru and MoRD



Note: The heatmaps display the regression results from the interaction of macroprudential indicators (LSTI, LTI, and LTV) with the mortgage rate differential (MoRD). Darker colors (more red) indicate a higher probability of refinancing. In other words, it typically increases with a rising MoRD and with increasing client indebtedness or monthly payments.

[12] We also interacted `MoRD` with `Net_Income` and `Loan_Size`. Both heatmaps (Figure B1) show that the probability of refinancing increases as `MoRD` rises, with the upper portions of the panels turning red. This suggests that a larger gap between the contractual rate and the prevailing market rate leads to a higher likelihood of refinancing. In the income-based heatmap, lower-wage borrowers are notably more sensitive to changes in `MoRD`, indicating that even modest payment savings may prompt refinancing decisions. Although larger loan sizes typically drive refinancing due to greater absolute savings, the loan-size heatmap reveals that borrowers with smaller loans also surprisingly exhibit significant sensitivity to `MoRD` shifts.

[13] We conducted the same exercise using `expR` instead of `MoRD` as the interacted variable in the nonlinear specifications. The resulting heatmaps revealed much weaker nonlinear patterns. While refinancing probabilities remained higher for borrowers with elevated macroprudential indicators (`LSTI`, `LTI`, and `LTV`), `expR` did not exhibit the same degree of sensitivity across these dimensions. These results are available upon request.

Table 2: Baseline Logit Model Results with Marcoprudential Indicators in Non-Linear Form

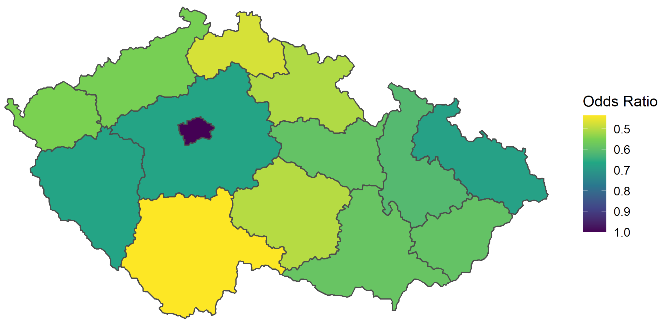
	Dependent variable: Refinancing Decision (1 = Refinanced, 0 = Not)					
	(1)	(2)	(3)	(4)	(5)	(6)
expR	0.210***	0.210***	0.212***	0.212***	0.216***	0.214***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
MoRD	0.037***	0.042***	0.061***	0.060***	0.042***	0.031**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
LSTI 15-20	0.152***					
	(0.022)					
LSTI 20-25	0.195***					
	(0.023)					
LSTI 25-30	0.188***					
	(0.025)					
LSTI 30+	0.113***					
	(0.022)					
LSTI		0.030***				
		(0.0024)				
LSTI^2		−0.00053***				
		(0.00005)				
LTI 1.5-3			0.375***			
			(0.029)			
LTI 3-5			0.517***			
			(0.028)			
LTI 5-6.5			0.596***			
			(0.031)			
LTI 6.5+			0.513***			
			(0.032)			
LTI				0.202***		
				(0.011)		
LTI^2				−0.0152***		
				(0.0010)		
LTV 50-60					0.243***	
					(0.034)	
LTV 60-70					0.305***	
					(0.030)	
LTV 70-80					0.378***	
					(0.026)	
LTV 80+					0.609***	
					(0.025)	
LTV						0.009***
						(0.002)
LTV^2						0.00002
						(0.00002)
Constant	−13.29***	−13.53***	−13.69***	−13.74***	−13.63***	−13.98***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)
Other Covariates	YES	YES	YES	YES	YES	YES
Region Controls	YES	YES	YES	YES	YES	YES
Year Controls	YES	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES	YES
Observations	3,261,928	3,261,928	3,261,928	3,261,928	3,261,928	3,261,928
Log Likelihood	−104,100	−104,068	−103,918	−103,938	−103,806	−103,788
Akaike Inf. Crit.	208,283	208,215	207,920	207,955	207,695	207,655

Note: *p<0.05; **p<0.01; ***p<0.001. Each column (1–6) shows a logit specification estimating the probability of refinancing (1 = yes, 0 = no). The main predictors are the mortgage rate differential (MoRD) and the expected rate change (expR), alongside borrower-level covariates. All columns include region, year, and bank fixed effects. Coefficients are log-odds; Standard errors (in parentheses) are clustered at the loan level.

5.2 Regional Variation

In the baseline regression (Table 1), we include regional fixed effects. Analysis of these effects reveals significant regional differences relative to Prague, as shown in Figure 6.[14] For instance, households in Jihočeský region (southern area tinted yellow) have about 56% lower odds of refinancing a mortgage loan compared to households in Prague (small dark blue area in the middle), while in Moravskoslezský kraj (north-eastern area tinted dark green) have only 32% lower odds relative to Prague. These disparities likely stem from heterogeneity in local housing markets, borrower characteristics, and the distribution of banking services that is not fully captured by our controls and fixed effects.[15]

Figure 6: Regional differences in the odds of refinancing



Note: The map illustrates how refinancing odds vary by region relative to Prague as the reference area (in dark blue), which equals 1. Lighter colors (green to yellow) indicate lower odds ratios, meaning households in those regions are less likely to refinance compared to households in Prague. Darker shades (trending toward dark blue) represent higher odds ratios, indicating a greater likelihood of refinancing relative to the reference category.

5.3 Future Horizons Variation

Table 3 shows logit estimates using different assumptions about future interest rates. In our baseline specification, the independent variable `expR` corresponds to a nine-month projection of the PRIBOR rate, but here we also estimate six- and twelve-month horizons (top panel) and a “perfect” future measure (bottom panel). These latter measures derive from actual ex-post average mortgage interest rates, shifted by the corresponding number of months. Specifically, for each loan origination month t, we compare the average mortgage interest rate at $t+x$ months to the average mortgage interest rate at t.

Across all horizons, the coefficient on the expected (or “perfect”) future rate differential remains significantly positive, suggesting that borrowers do respond to perceptions or realizations of rising interest rates. The effect is especially pronounced at the nine- and twelve-month marks, where the estimated coefficients exceed 0.20 and 0.40, respectively. In the “perfect” future specification, we see a similarly strong positive impact, confirming that even when using ex-post observed interest rates, borrowers appear to act as if they anticipate higher future costs. The findings indicate that the baseline nine-month forecast captures the general behavior well, yet the direction and significance of the relationship remain stable under alternative horizons or data-driven constructions of future

[14] Complete regional results appear in Table B1 in the Appendix.
[15] All our models also include year and bank controls to account for time-specific and institutional factors.

rates. All regressions include the same additional controls (loan-level attributes, region fixed effects, year effects, and bank dummies), so the variation across columns reflects how different interest-rate horizons shape refinancing decisions, rather than broader changes in economic conditions or institutional factors.

Table 3: Logit Model Results for Different Future Horizons

	Dependent variable:		
	Refinancing Decision (1 = Refinanced, 0 = Not)		
	(6M)	(9M)	(12M)
expR	0.033	0.210^{***}	0.401^{**}
	(0.020)	(0.026)	(0.028)
Other covariates	YES	YES	YES
Region controls	YES	YES	YES
Year controls	YES	YES	YES
Bank Controls	YES	YES	YES
Observations	3,261,928	3,261,928	3,261,928
Log Likelihood	−104,058	−104,026	−103,949
Akaike Inf. Crit.	208,195	208,131	207,977

	Dependent variable:		
	Refinancing Decision (1 = Refinanced, 0 = Not)		
	(6M)	(9M)	(12M)
Perfect_Future	0.088^{***}	0.085^{***}	0.179^{**}
	(0.019)	(0.015)	(0.015)
Other covariates	YES	YES	YES
Region controls	YES	YES	YES
Year controls	YES	YES	YES
Bank Controls	YES	YES	YES
Observations	3,261,928	3,261,490	3,253,707
Log Likelihood	−104,048	−104,040	−103,859
Akaike Inf. Crit.	208,176	208,160	207,798

Note: *p<0.05; **p<0.01; ***p<0.001. Both panels display logit estimations where the dependent variable is whether a mortgage was refinanced (1) or not (0). In the top panel, expR measures the expected change in interest rates over 6, 9, or 12 months. In the bottom panel, Perfect_Future is an ex-post measure capturing the actual rate change over the same horizons. In each case, other loan- and borrower-level controls are included (not shown). Coefficients are log-odds; Standard errors (in parentheses) are clustered at the loan level.

6. Timing of Refinancing Decisions

While our panel logit framework shows which factors influence the probability of refinancing at any point during the fixation period, it does not pinpoint *when* in that period refinancing is most likely to take place. We therefore adopt two survival analysis methods—the Kaplan–Meier (KM) estimator and the Cox proportional hazards model—to examine the timing dimension of refinancing. The KM curves provide a non-parametric depiction of the fraction of loans that remain unrefinanced over time, while the Cox model estimates how each covariate affects the instantaneous hazard (rate) of refinancing. This survival-based approach captures the dynamics of refinancing behavior, complementing our earlier (logit-based) analysis of which loans are likely to refinance.

For the survival analysis, we implement a *start–stop* Cox model using monthly observations for every mortgage loan. Specifically, each mortgage loan i appears as a sequence of monthly intervals from origination until either (i) the loan refinances (the event), or (ii) the fixation period ends (censoring).

In this framework, *time* (the baseline time scale) accumulates continuously in months since loan origination. For each monthly interval (start to stop), we note whether the borrower refinances at the end of that interval (event = 1) or remains outstanding (event = 0). Critically, variables such as the mortgage rate differential (`MoRD`) and the expected short-term rate (`expR`) are updated each month in line with observed market conditions, ensuring that the hazard at any point reflects the *current* environment. Borrower characteristics that are largely time-invariant (e.g. age at origination) enter once.[16]

6.1 Survival Patterns

To gain an initial, unadjusted view of how long loans remain unrefinanced, we plot a series of Kaplan–Meier (KM) curves. Unlike the Cox model, which isolates the effect of specific covariates, the KM estimator simply reports the empirical survival function—that is, the probability (or proportion) of loans that remain unrefinanced at each point in time. Since we are now observing the time until refinancing, we distinguish between different fixation periods. Here, we focus primarily on five-year fixation loans (the most common in our dataset), defining `time` as the number of days from origination to either the refinancing event (if it occurs) or the end of the fixation period (censoring).[17]

First, we stratify KM curves by key borrower or loan characteristics (Figure 7), including `LSTI`, `LTI`, and `LTV` brackets, as well as categories for `log(Loan_Size)`, `log(Net_Income)`, `Age_Client`, the mortgage rate differential (`MoRD`) and expectations about the rates (`expR`). This allows us to compare survival patterns across distinct subpopulations. Each curve plots the fraction of loans that remain *unrefinanced* (on the vertical axis) against the number of months since

[16] This panel-based *start–stop* design captures within-fixation dynamics more precisely than a single-record "collapsed" approach, since each interval's hazard depends on *contemporaneous* covariate values. Although more computationally intensive, this model more directly links monthly interest-rate movements and other evolving factors to the decision to refinance, yielding a richer depiction of the timing of refinancing events. We, however, also test a "collapsed" version of this model in the robustness section, section 7.

[17] Figure B4 shows the baseline KM curves for all fixations, revealing the overall speed at which households refinance. A sharper descent indicates more frequent refinancing activity. Although the 4-year fixations have the widest confidence intervals (due to the relatively small sample of such loans), their shape aligns with the other fixation curves, supporting the stability and robustness of our findings.

origination (horizontal axis). A *steeper* drop in any survival curve indicates *faster* refinancing (i.e. a larger fraction of loans that exit earlier).

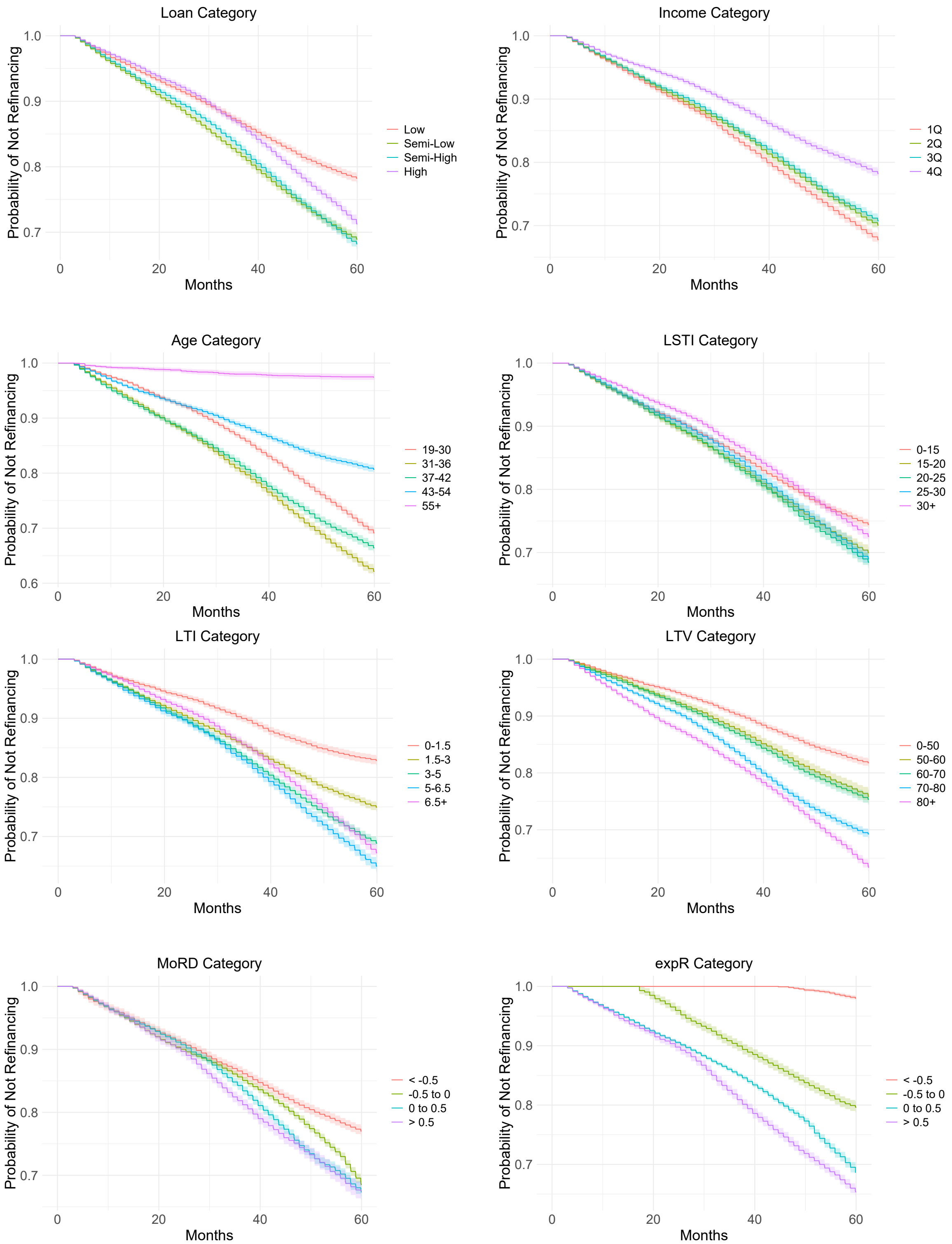
We split loans into four categories (from low to high) based on original amounts. The survival curve for higher-amount loan categories descends more steeply, indicating that borrowers with larger loans tend to refinance *earlier*—consistent with the potential for larger interest-cost savings. Interestingly, the very high loan category (4th quartile, High) shows a steep decline that occurs later than in the intermediate categories. Conversely, comparing high- versus low-income households reveals a faster drop for the lower-income groups than for the richest households (4th quartile), suggesting that the former refinance *sooner*. Age also exhibits noticeable effects: younger borrowers show a steeper initial slope (faster refinancing), while older cohorts display a more gradual decline. Notably, refinancing is extremely low for borrowers up to age 55, suggesting that other factors may be at play.

Categorizing by *LSTI*, *LTI*, and *LTV* indicates that higher ratios tend to prompt earlier refinancing, reflecting a greater urgency to reduce mortgage-payment burdens relative to income or equity. Interestingly, for LTI above 6.5 the probability of non-refinancing is lower than for the next tier (LTI 5–6.5), probably because refinancing may still pose difficulties for more indebted households (as discussed in the previous chapter).

We also stratify by `MoRD` and `expR` brackets (approximately quartiles). Borrowers with a higher `MoRD` refinance *earliest*, as the payoff is greater when the gap between the contract rate and the market rate is large. For `expR`, those anticipating higher future rates generally refinance sooner, whereas borrowers in categories with `MoRD` less than -0.5—who are expecting a drop in rates—almost never refinance and possibly wait.

Overall, the KM curves suggest that households facing stronger financial incentives or constraints (e.g., high debt ratios, larger loan balances, high mortgage rate differentials, or steep expected rate increases) tend to refinance *earlier*. In the subsequent Cox proportional hazards analysis, we examine whether these patterns persist when controlling for multiple covariates simultaneously.

Figure 7: Survival Curves



Note: Each panel depicts the Kaplan–Meier (KM) estimate of the *Probability of Not Refinancing* over time (on the y-axis) for a given categorical grouping. The x-axis shows elapsed days since loan origination, and each step down in the KM curve indicates occurrence of the refinancing event. The vertical distance between curves reflects differences in refinancing rates across categories: a steeper drop implies faster refinancing in that group. The shaded bands represent approximate pointwise 95% confidence intervals.

6.2 Cox Hazard Model Results

Table 4 presents estimates from our start–stop Cox hazard model. In this framework, a coefficient (hazard ratio) above 1 indicates a *higher* hazard of refinancing (i.e., *faster* refinancing), whereas a value below 1 implies *slower* refinancing. For instance, a hazard ratio of 1.20 suggests that the instantaneous likelihood of refinancing at any point in time is 20% higher for a one-unit increase in the variable of interest (for continuous variables) or 20% higher relative to the baseline category (for categorical variables).

Across all specifications, both `MoRD` (the difference between the borrower's mortgage rate and the prevailing market mortgage rate) and `expR` (the gap between the prevailing market rate and expected interest rates in nine months) exhibit hazard ratios well above 1. Column 1 replicates the model from Table 1, showing that a 1 percentage point increase in `MoRD` raises the refinancing hazard by 16%, with a similar effect for `expR`. Column 5, which excludes Prague, shows consistent results, though the effect of `expR` appears somewhat stronger.

Next, we analyze the brackets of `MoRD` and `expR` to complement our Kaplan–Meier (KM) curve results. For example, a bracket such as `MoRD: 0 to 0.5` with a hazard ratio of 1.25 implies a 25% higher refinancing hazard throughout the fixation period compared to the baseline (`MoRD` < -0.5). Similarly, borrowers with `expR > 0.5` refinance earlier on average, confirming that expectations of rising interest rates accelerate refinancing behavior.

For debt-service ratios (`LSTI`, `LTI`) and loan-to-value (`LTV`), higher brackets—relative to their respective baselines (`LSTI` : 0–15, `LTI` : 0–1.5, `LTV` : 0–50)—are positively associated with refinancing speed. For instance, `LTI` : 6.5+ with a hazard ratio of 1.70 suggests that heavily indebted households face a 70% higher refinancing hazard than those in the lowest bracket, likely due to stronger incentives to reduce monthly payments. However, for very high `LSTI` or `LTI` values, the hazard ratio begins to decline, indicating that severe credit constraints or limited equity can delay refinancing despite the potential incentives.

`Loan_Size` consistently exhibits hazard ratios above 1, reflecting that borrowers with larger loans refinance sooner, likely because interest-cost savings are more substantial. In contrast, `Net_Income` shows hazard ratios below 1 across all columns, indicating that wealthier borrowers may face less urgency to refinance. Age effects (`Age_Client` and its square) reveal a nonlinear relationship: while the linear term suggests that older borrowers refinance sooner, the negative squared term indicates diminishing and eventually negative effects beyond a certain age (mid-50s to 60s, depending on specification). Finally, borrowers who do not use external brokers (`Broker_No`) refinance more slowly (hazard ratio below 1), possibly due to less external guidance or fewer incentives to refinance. The role of brokers, and the mechanisms that may drive these differences, is examined in more detail in the following chapter on model extensions.

We verify the proportional hazards assumption using both graphical analysis of Schoenfeld residuals and formal tests (see Table B2). For most variables, including `MoRD` and `expR`, the residuals remain stable over time, though a few outliers appear for `expR`. The tests indicate that while `MoRD`, `expR`, and other primary predictors meet the assumption ($p > 0.05$), some covariates—such as `Loan_Size`, `Age`, and categorical variables—do not. This likely reflects the discrete nature of these covariates, for which stratification may provide a more appropriate specification.

Table 4: Cox Proportional Hazard Models

	Dependent variable:						
	Time to Event						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MoRD	1.160***	1.135***	1.161***	1.136***	1.149***		1.145***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)		(0.012)
MoRD: -0.5 to 0						1.107***	
						(0.025)	
MoRD: 0 to 0.5						1.274***	
						(0.029)	
MoRD: >0.5						1.458***	
						(0.033)	
expR	1.163***	1.161***	1.161***	1.165***	1.194***	1.206***	
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.025)	
expR: -0.5 to 0							2.148***
							(0.082)
expR: 0 to 0.5							2.558***
							(0.084)
expR: >0.5							2.722***
							(0.083)
LSTI 15–20		1.174***					
		(0.024)					
LSTI 20–25		1.233***					
		(0.024)					
LSTI 25–30		1.219***					
		(0.026)					
LSTI 30+		1.153***					
		(0.023)					
LTI 1.5–3			1.458***				
			(0.032)				
LTI 3–5			1.691***				
			(0.031)				
LTI 5–6.5			1.841***				
			(0.033)				
LTI 6.5+			1.697***				
			(0.033)				
LTV 50–60				1.284***			
				(0.035)			
LTV 60–70				1.369***			
				(0.031)			
LTV 70–80				1.574***			
				(0.027)			
LTV 80+				1.639***			
				(0.026)			
log(Net_Income)	0.748***				0.769***	0.749***	0.750***
	(0.018)				(0.020)	(0.018)	(0.018)
log(Loan_Size)	1.236***				1.238***	1.237***	1.233***
	(0.013)				(0.014)	(0.013)	(0.013)
Age_Client	1.546***	1.539***	1.536***	1.530***	1.541***	1.547***	1.546***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Age_Client^2	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Broker_No	0.817***	0.786***	0.818***	0.804***	0.833***	0.818***	0.817***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.019)	(0.019)
Employee_Yes	3.509***	3.471***	3.484***	3.418***	4.044***	3.519***	3.509***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.033)	(0.027)	(0.027)
Region, Bank and Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,926,954	2,926,954	2,926,954	2,926,954	2,553,853	2,926,954	2,926,954
Concordance (Harrell's C)	0.729	0.727	0.730	0.730	0.721	0.729	0.730
Likelihood Ratio Test	11,794	11,522	11,847	11,854	9,336	11,808	11,903
Score (logrank) Test	9,308	9,062	9,358	9,387	7,305	9,310	9,362

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. The dependent variable in these Cox regressions is the *time to event* (time until refinancing). The reported coefficients in the table are $\exp(\hat{\beta})$ (hazard ratios). A hazard ratio above 1 means that a one-unit increase in the covariate *increases* the hazard (and thus shortens the expected time-to-event), while a hazard ratio below 1 indicates a *decrease* in the hazard. Standard errors (in parentheses) are clustered at the loan level.

7. Robustness and Extensions

First, in addition to the main logistic regression, we estimate a Linear Probability Model (LPM) using the same dataset and explanatory variables. Interpreting the LPM coefficients is straightforward: each coefficient corresponds to a percentage-point change in the refinancing probability for a one-unit increase in the relevant explanatory variable.

The LPM results (Table B3) broadly align with those of the baseline logistic model (Table 1), lending credibility to our main findings. To assess validity, we tested the LPM's predicted values and observed that approximately 9.8% lie outside the valid probability range of [0,1]. This underscores why we report LPMs only as a supplementary check for binary outcomes. While the LPM provides a simple and interpretable benchmark, our primary inferences are grounded in the logistic regression, which ensures predicted probabilities remain strictly between zero and one. Other results employing the LPM, including all the specifications corresponding to Table 2, Table 3, Table B1 and Table B2 are available upon request.

Second, we investigate broker usage in more detail. Figure B5 plots Kaplan–Meier survival curves by broker status. Broker-intermediated loans refinance more quickly overall, but the divergence from non-broker loans becomes pronounced only after roughly 12–24 months. A plausible institutional explanation is the commission–clawback window embedded in many broker–lender contracts, which requires brokers to repay part of their initial commission if the loan is refinanced too early. This creates a clear disincentive to recommend refinancing in the first years of the fixation spell. As a result, refinancing behaviour is similar across groups early on, with broker effects emerging *more clearly* once the clawback window expires and refinancing becomes economically attractive.

Table B4 examines a complementary dimension of broker use through interaction terms in the panel logit model. Brokers do not materially amplify refinancing responses to contemporaneous rate differentials (`MoRD`); the interaction effects are small and statistically insignificant. By contrast, brokers meaningfully strengthen the response to expected future rate increases (`expR`). Quantitatively, the coefficient on `expR` for broker-assisted loans is about 0.235, whereas for non-broker loans it is lower by roughly 0.084, implying an effective sensitivity of about 0.151. Thus, non-broker borrowers exhibit only about two-thirds of the forward-looking responsiveness of broker-assisted households. This pattern suggests that broker effects operate primarily through enhanced interpretation of forward-looking information, rather than through mechanical responses to current rate differentials.

Third, for the survival analysis, we tried to collapse each mortgage loan into a single observation rather than use multiple monthly records. Concretely, for each loan i, we keep only the row in which the loan is refinanced (event), if it occurs, or the final row of the fixation period if it does not refinance (censoring). We then define *time* as the number of days from origination to the refinancing event (or to fixation end), and we set an event indicator to 1 for refinancing and 0 otherwise.

This "collapsed" approach could be chosen to avoid the steep computational burden that a fully panelized (start–stop) Cox model would impose, especially given monthly time-varying covariates. This approach aligns more closely with the standard Cox proportional hazards model (Cox, 1972) and allows us to validate that the findings from our more flexible start-stop specification are not driven by the underlying panel structure. A drawback, however, is that we lose finer within-fixation dynamics for variables such as the mortgage rate differential (`MoRD`) and the short-term rate (`expR`), which change over time in the underlying panel. In the collapsed data, these rate measures are averaged out for every household. Consequently, the model uses a single observed value for the mortgage rate differential (`expR`) and the projected short-term rate (`MoRD`), rather than capturing how they might evolve month by month. Other characteristics, like borrower age or income, remain time-invariant in our dataset and thus are less affected by this simplification. The results (Table B5) roughly corespond to our baseline start–stop Cox model, but coefficients for (`expR`) and (`MoRD`) differs substantially, yet remain significant and correctly signed.

Fourth, we apply stratification to our Cox proportional hazards (PH) models to accommodate potential heterogeneities in the baseline hazard across different categorical variables. This approach is motivated by the possibility that certain covariates—such as broker usage, employment status, or bank identifier—may not fully meet the proportional hazards assumption if forced to share a single underlying hazard function (Lin and Zelterman, 2002; Kalbfleisch and Prentice, 2002). By stratifying on these variables, we allow each category to have its own baseline hazard, effectively removing the need to estimate a single hazard function across potentially distinct groups of borrowers. As reported in Table B6, the hazard ratios for `MoRD`, `expR`, and other key variables remain largely consistent with our baseline across different model specifications, reinforcing the idea that interest-rate incentives and borrower-level factors drive refinancing behavior, even when baseline hazards differ by broker usage, income source, or region.

Fifth, due to potential differences in refinancing behavior across various fixation periods, the data was categorized into 5-, 4-, and 3-year fixation groups. We have also estimated all the regressions for 3-year fixations (mortgage loans with 4-year fixations are very limited), and the results roughly correspond to our 5-year baseline fixations. Results are available upon request.

Sixth, we re-estimate the baseline logit model using an extended sample which contains a lower number of refinanced loans (due to the additional matching condition based on the structure of loan repayments, see Section 3.1), but a higher number of non-refinanced loans resulting from the relaxation of the matching criterion, whereby loans are classified as non-refinanced only after the second matching round rather than after the first. Compared to the baseline sample, a large share of previously ambiguous loans is thus reclassified as non-refinanced. Across all specifications, the key explanatory variables, particularly `MoRD`, income, loan size, macroprudential indicators, and borrower age, retain their signs and remain highly statistically significant, confirming that our core findings are robust to major changes in sample composition (Table B7). The coefficient on `expR` remains correctly signed but is not always statistically significant in the enlarged dataset, a pattern consistent with the weaker predictive power of short-term rate expectations relative to the mortgage rate differential.[18] Differences in coefficient magnitudes relative to the baseline could, in principle, arise mechanically from the substantially lower unconditional refinancing rate in the expanded sample, which could inflate log-odds coefficients when the event becomes rarer. Crucially, when comparing *marginal effects*, computed as $\partial p/\partial x = \beta \times p(1-p)$, rather than raw log-odds, the estimated economic effects would be expected to remain very similar across our two samples, although computing marginal effects at this scale would be computationally demanding given the size of our dataset.

[18] We also test alternative horizons for the expected rate change. Replacing `expR, 9M` with `expR, 6M` yields insignificant coefficients across all specifications, whereas the 12-month measure `expR, 12M` is consistently significant at least at the 5% level in all five baseline regressions. This suggests that longer forward-looking horizons may capture expectations more effectively than shorter ones, while leaving the broader interpretation of refinancing incentives intact.

8. Conclusions

This paper demonstrates that refinancing decisions are strongly influenced by the mortgage rate differential—that is, the difference between the borrower's current mortgage rate and the average prevailing market mortgage rate—and by anticipated future interest rate changes. Households adjust their mortgage portfolios in response to shifts in market conditions, reinforcing the idea that monetary policy, even in a market dominated by fixed-rate products with short-term fixations, is effectively transmitted through borrower behavior. In particular, when policy-induced changes widen the gap between contractual and prevailing rates, borrowers are more inclined to refinance, thus accelerating the transmission of monetary policy. This effect is further amplified by borrowers' forward-looking expectations. If households expect future rates to be higher, they tend to act preemptively to secure lower current rates. When aggregated, this behavior provides central banks with valuable insights into the real effectiveness of their policy signals.

From a macroprudential and financial stability perspective, our analysis indicates that borrowers with higher financial burden (reflected in moderate-to-high LSTI, LTI, or LTV) are especially sensitive to rate changes, often refinancing during periods of lower interest rates. Paradoxically, those with extremely high debt ratios may be constrained by stricter lending standards and thus refinance less often, underscoring how risk can concentrate among a subset of borrowers unable to benefit from favorable rate environments. While substantial refinancing activity among indebted households could potentially lead to a concentration of loan contracts whose fixed-rate periods expire at the same time, our evidence shows that forward-looking borrowers sometimes refinance preemptively ahead of interest rate increases, thereby partially smoothing large waves of simultaneously expiring fixed-rate terms. This interplay between responsive households and those left behind by credit constraints can shape the distribution of refinancing timelines, influencing both the incidence of rate shocks and their aggregate impact on financial stability. Importantly, our findings offer valuable tools for anticipating the potential timing and intensity of refinancing waves. By identifying borrower profiles and interest rate differentials most likely to trigger early refinancing, policymakers can better monitor periods of elevated risk associated with large numbers of fixed-rate loan contracts reaching the end of their fixation period simultaneously, and proactively consider mitigating strategies such as targeted communication or fine-tuning of macroprudential tools.

Methodologically, the combined use of panel logit and Cox proportional hazards models in this paper offers a robust framework that captures both the determinants and the timing of refinancing events. This dual approach highlights the nuanced interplay between borrower characteristics—such as income level, age, and loan size—and their sensitivity to current and anticipated monetary conditions. It provides a comprehensive understanding of refinancing dynamics, demonstrating that even within a seemingly homogeneous market, individual differences play a critical role in shaping refinancing behavior. These integrated insights can be useful for central banks aiming to balance short-term market adjustments with the long-term goal of financial stability.

Future research could explore the longer-term consequences of refinancing for household balance sheets and consumption patterns, especially under scenarios of repeated interest rate shocks. It would also be valuable to examine how refinancing interacts with housing market dynamics—for instance, whether borrowers who refinance are also more likely to move, upgrade homes, or extract equity. Additionally, cross-country comparisons could shed light on how institutional settings, legal frameworks for prepayment, and financial literacy influence refinancing responsiveness. Finally, structural modeling of borrower behavior under different policy regimes could help evaluate the macroeconomic and financial stability trade-offs associated with facilitating or constraining early refinancing.

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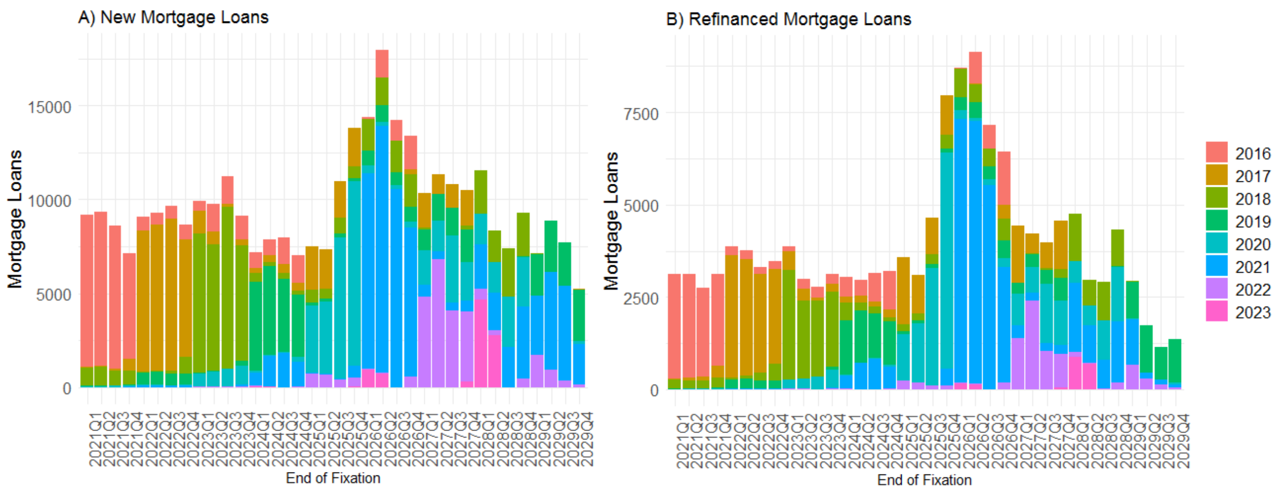
Appendix A: Appendix

Figure A1: New and Refinanced Mortgage Loans Fixation Periods



Note: The panel A assumes that there is no early repayment or refinancing of the existing loan (at another bank) and the loan will be fully refinanced at the end of the fixed period. Early repayment or refinancing of the loan before the end of the fixed period would result in a smaller volume of fixed-endings in the particular years. Thus, the panel A represents more of an upper bound for the number of fixed-endings in individual years and quarters. On the other hand, the analysis does not account for loans with shorter fixed periods that will be granted in the following years, which will increase the refinancing volume. For panel B, the same principle applies. That is, a refinanced mortgage loan can also be refinanced again, and it does not necessarily have to be re-fixed only at the end of the fixation period.

Table A1: Number, Share, and Cumulative Share of New Mortgage Loans by Fixation

Fixation (years)	Number of loans	Share (%)	Cumulative Share (%)
1	7,915	1.16	1.16
2	3,853	0.56	1.72
3	86,654	12.69	14.42
4	2,860	0.42	14.83
5	331,162	48.50	63.34
6	33,043	4.84	68.18
7	72,925	10.68	78.86
8	66,719	9.77	88.63
9	562	0.08	88.71
10	74,039	10.84	99.55
Over 10	3,040	0.45	100.00

Table A2: Descriptive Statistics of New Mortgages (2016–2018)

Variable	**Mean**		**SD**		**Min**		**Max**		**Median**		**Skewness**		**Kurtosis**	
	Ref = 1	Ref = 0	Ref = 1	Ref = 0	Ref = 1	Ref = 0	Ref = 1	Ref = 0	Ref = 1	Ref = 0	Ref = 1	Ref = 0	Ref = 1	Ref = 0
Numerical Variables														
MoRD (inception)	0.07	0.13	0.54	0.56	-1.38	-1.55	8.01	7.95	-0.05	-0.01	4.26	3.53	32.30	21.80
expR (in 9 M) (inception)	0.21	0.22	0.21	0.21	0.01	0.01	0.56	0.56	0.10	0.10	0.51	0.45	1.68	1.66
MoRD (refinancing)	-0.18	-1.80	0.87	1.59	-3.96	-4.55	8.05	7.98	-0.17	-2.13	0.07	0.42	9.74	2.19
expR (in 9 M) (refinancing)	0.31	-0.13	0.41	1.11	-4.40	-4.40	1.23	1.23	0.29	-0.15	-0.36	-1.38	8.47	1.66
log(Net_Income)	13.00	13.10	0.52	0.64	10.40	10.10	16.20	17.70	12.90	13.00	0.71	0.94	4.66	5.46
log(Loan_Size)	14.30	14.20	0.69	0.82	10.80	10.80	16.50	18.10	14.30	14.20	-0.60	-0.26	3.90	3.42
Age_Client	35.50	39.00	7.27	10.50	20.00	18.00	62.00	87.00	35.00	38.00	0.43	0.28	2.60	2.26
Age_Client^2	1310	1630	542	856	400	324	3844	7569	1225	1444.00	0.86	0.75	3.44	3.03
Broker_No	0.25	0.32	0.43	0.47	0	0	1	1	0	0	-1.15	-0.77	2.32	1.59
Employee_Yes	0.90	0.71	0.30	0.45	0	0	1	1	1	1	-2.74	-0.92	2.32	1.59
LSTI	21.30	21.30	10.70	12.20	0.99	0.99	82.80	83.20	20.40	19.60	0.58	0.75	3.49	4.25
LTI	4.43	3.84	2.39	2.51	0.15	0.12	17.70	17.70	4.17	3.39	0.65	0.92	3.45	3.87
LTV	73.60	66.20	18.70	21.80	5.13	5.00	122.00	122.00	80.00	70.70	-1.05	-0.73	3.98	2.78

Variable	**Modus**	
	Ref = 1	Ref = 0
Categorical Variables		
Year (inception)	2017	2016
Bank Size (inception)	Medium	Medium
Year (refinancing)	2021	2022
Bank Size (refinancing)	Large	-

Notes: Some variables in this table are measured at different time points—at inception and at refinancing. This applies to the MoRD and expR variables, as well as to bank affiliation and year, which are recorded both at inception and at refinancing (or refixing if the client remains with the original bank). In contrast, key borrower characteristics (e.g., age, net income) and macroprudential indicators are captured only at loan inception because continuous updates are not available. This distinction should be taken into account when interpreting the descriptive statistics.

Table A3: Variables Description

Variable	Description
`Refinanced`	Dependent variable; equals 1 if the loan was refinanced during the fixation period (in a given month), 0 otherwise.
`MoRD`	Mortgage rate differential: the difference between the borrower's individual mortgage rate and the average prevailing market mortgage loan rate in a given month. Calculated as $\texttt{Rate}_i - \texttt{MarketRate}_t$. Updated monthly.
`expR`	Expected interest rate change: forward-looking measure based on the projected difference between the PRIBOR rate in 6 to 12 months and the current PRIBOR. Calculated as $\texttt{PRIBOR}_{t+x} - \texttt{PRIBOR}_t$, with the baseline horizon at 9 months. Recalculated each month.
`LSTI`	Loan service-to-income ratio: monthly mortgage payment as a share of monthly income.
`LTI`	Loan-to-income ratio: total loan amount divided by annual income.
`LTV`	Loan-to-value ratio: loan size relative to the property's appraised value at origination.
`Age_Client`	Borrower's age at the time of mortgage origination.
$\texttt{Age\_Client}^2$	Square of borrower's age to capture non-linear age effects.
`log(Net_Income)`	Logarithm of borrower's monthly net income at origination.
`log(Loan_Size)`	Logarithm of the mortgage loan amount.
`Broker_No`	Equals 1 if borrower did not use a broker; 0 if broker-assisted.
`Employee_Yes`	Equals 1 if borrower is a salaried employee; 0 otherwise (self-employed).
`Region`	Categorical variable indicating borrower's region of residence (regional fixed effects).
`Bank`	Categorical variable indicating the originating bank (bank fixed effects).
`Year`	Categorical variable for the fixation year (year fixed effects).

Appendix B: Regressions

Table B1: Fixed Effects for Regions from Table 1

	Dependent variable:				
	Refinancing Decision (1 = Refinanced, 0 = Not)				
	(1)	(2)	(3)	(4)	(5, without Prague)
Baseline:	Prague	Prague	Prague	Prague	Jihočeský region
Jihočeský region	-0.830^{***}	-0.799^{***}	-0.768^{***}	-0.835^{***}	
	(0.040)	(0.040)	(0.040)	(0.040)	
Jihomoravský region	-0.539^{***}	-0.499^{***}	-0.482^{***}	-0.515^{***}	0.296^{***}
	(0.031)	(0.030)	(0.030)	(0.030)	(0.041)
Karlovarský region	-0.596^{***}	-0.568^{***}	-0.522^{***}	-0.663^{***}	0.292^{***}
	(0.053)	(0.052)	(0.052)	(0.052)	(0.059)
region Vysočina	-0.690^{***}	-0.654^{***}	-0.622^{***}	-0.680^{***}	0.185^{***}
	(0.045)	(0.045)	(0.045)	(0.045)	(0.053)
Královéhradecký region	-0.678^{***}	-0.642^{***}	-0.611^{***}	-0.694^{***}	0.218^{***}
	(0.042)	(0.041)	(0.041)	(0.041)	(0.050)
Liberecký region	-0.747^{***}	-0.737^{***}	-0.703^{***}	-0.802^{***}	0.070
	(0.045)	(0.045)	(0.045)	(0.045)	(0.052)
Moravskoslezský region	-0.385^{***}	-0.354^{***}	-0.324^{***}	-0.416^{***}	0.500^{***}
	(0.033)	(0.033)	(0.033)	(0.033)	(0.042)
Olomoucký region	-0.486^{***}	-0.449^{***}	-0.417^{***}	-0.499^{***}	0.387^{***}
	(0.038)	(0.037)	(0.037)	(0.037)	(0.046)
Pardubický region	-0.531^{***}	-0.493^{***}	-0.465^{***}	-0.532^{***}	0.317^{***}
	(0.041)	(0.040)	(0.040)	(0.040)	(0.049)
Plzeňský region	-0.400^{***}	-0.370^{***}	-0.341^{***}	-0.412^{***}	0.481^{***}
	(0.038)	(0.037)	(0.037)	(0.037)	(0.046)
Středočeský region	-0.400^{***}	-0.372^{***}	-0.357^{***}	-0.404^{***}	0.482^{***}
	(0.028)	(0.027)	(0.027)	(0.027)	(0.036)
Ústecký region	-0.590^{***}	-0.583^{***}	-0.538^{***}	-0.684^{***}	0.274^{***}
	(0.038)	(0.038)	(0.038)	(0.038)	(0.046)
Zlínský region	-0.528^{***}	-0.483^{***}	-0.453^{***}	-0.514^{***}	0.335^{***}
	(0.039)	(0.038)	(0.038)	(0.038)	(0.048)
Observations	3,261,928	3,261,928	3,261,928	3,261,928	2,836,445
Log Likelihood	−103,917	−104,137	−104,051	−103,788	−89,579
Akaike Inf. Crit.	207,913	208,351	208,199	207,654	179,237

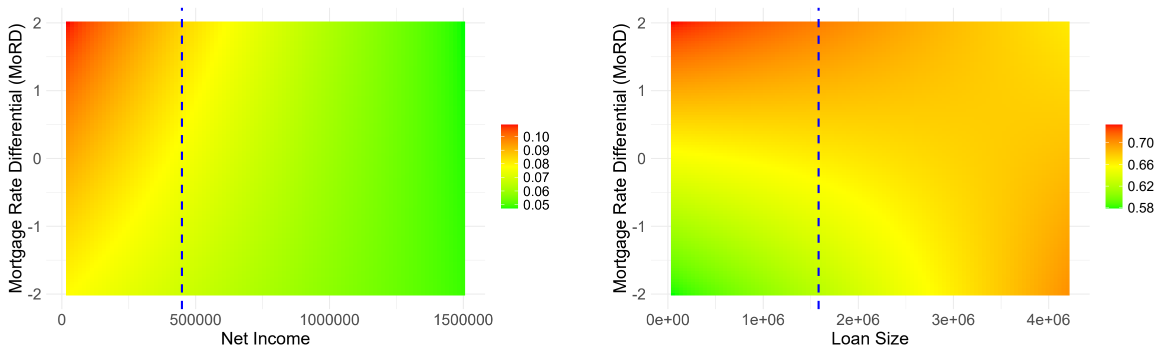
Note: *p<0.05; **p<0.01; ***p<0.001. Coefficients are log-odds; Standard errors (in parentheses) are clustered at the loan level.

Table B2: Logit Model with Bank-Size Variables

	Dependent variable:
	Refinancing Decision (1 = Refinanced, 0 = Not)
Medium bank (original)	-0.427^{***}
	(0.018)
Small bank (original)	0.623^{***}
	(0.037)
Medium bank (refin.)	0.487^{***}
	(0.018)
Small bank (refin.)	-1.082^{***}
	(0.047)
Baseline: Large bank	
Other covariates	YES
Region controls	YES
Year controls	YES
Bank controls	NO
Observations	3,261,928
Log Likelihood	-104,221
AIC	208508

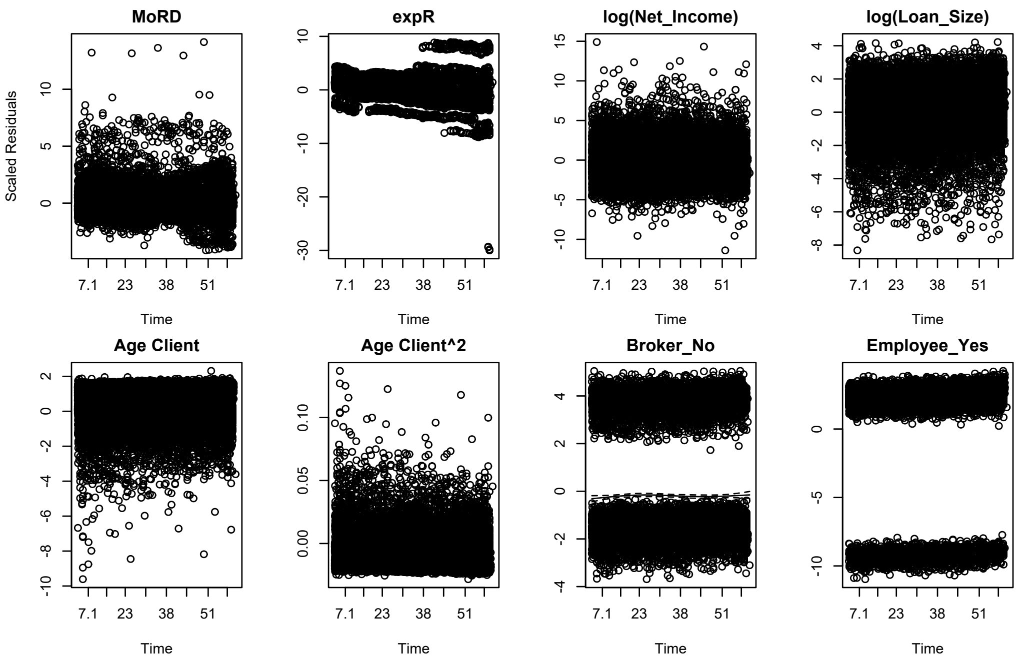
Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors (in parentheses) come from the single logit specification that includes bank-size (former) and bank-size (refinancing) relative to the omitted baseline of "Large bank." Additional variables from baseline Table 1 are included but not displayed.

Figure B1: Probability of Refinancing - Interaction of MPPs and MoRD



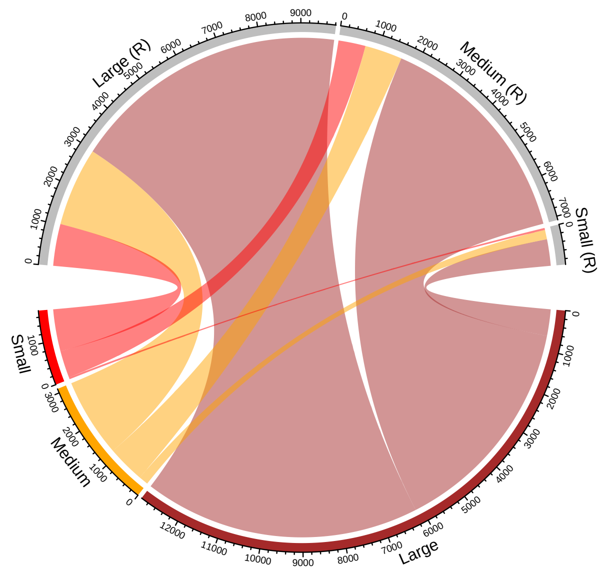
Note: The heatmaps display the regression results from the interaction of loan size and net income with the mortgage rate differential (MoRD). Darker colors (more red) indicate a higher probability of refinancing.

Figure B2: Schoenfeld Residual Plots for Testing the Proportional Hazards Assumption



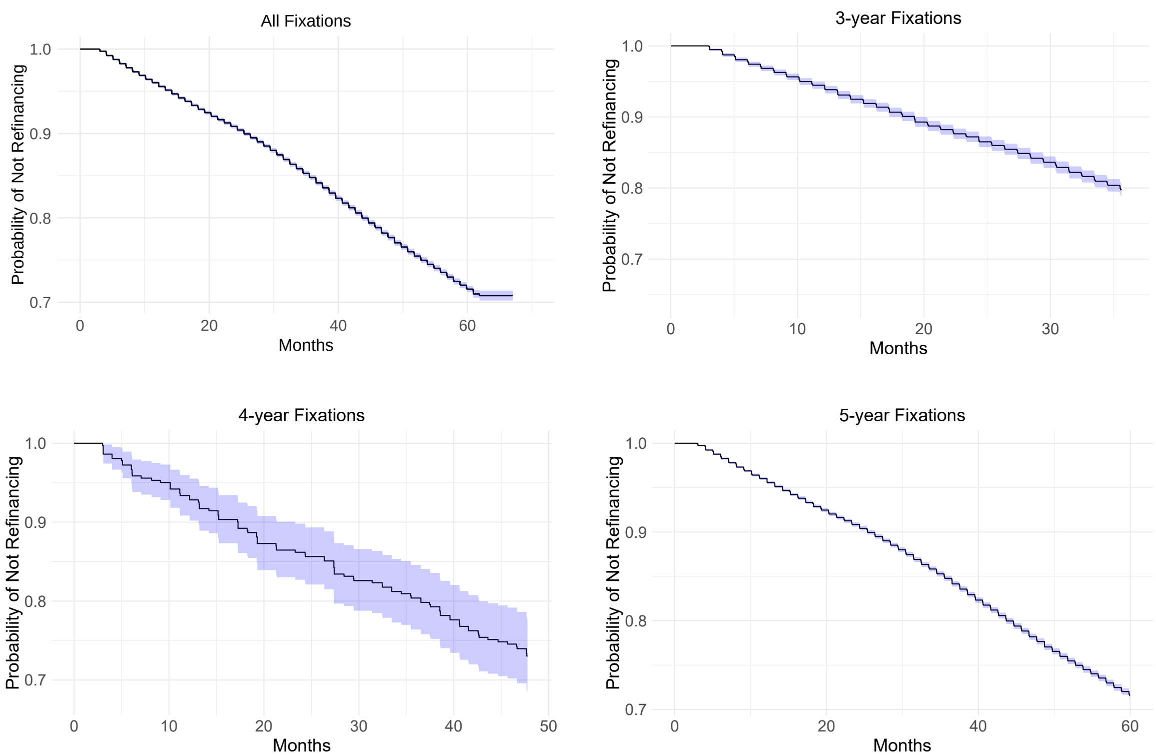
Note: Each panel shows the scaled Schoenfeld residuals over time (x-axis) for one covariate in Model 1 in Table 4. A perfectly horizontal trend around zero would indicate no systematic change in the log-hazard ratio over time. Substantial departures from zero suggest violation of the proportional hazards (PH) assumption for that covariate. Here, large or sloped residual patterns imply that the covariate's effect on the hazard may vary as time progresses.

Figure B3: Switching Between Banks when Refinancing



Note: Categories of banks by mortgage market share. The bottom part of the diagram denotes the bank's category when originating a loan and the top part of the diagram, denoted by the letter R in parentheses, shows the bank's category when refinancing.

Figure B4: Survival Curves



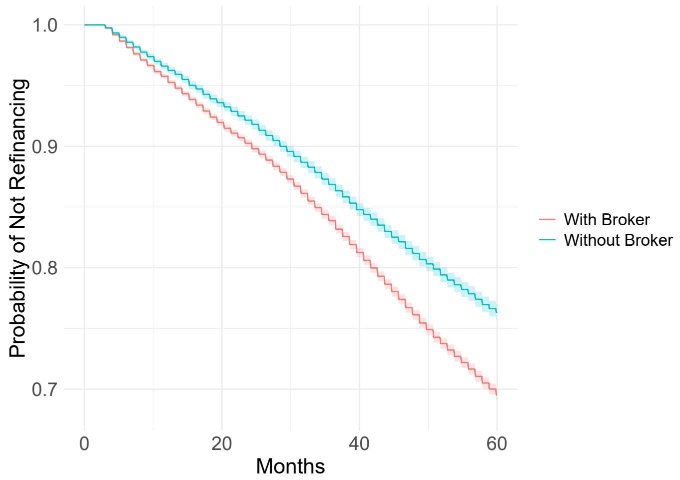
Note: Each panel depicts the Kaplan–Meier (KM) estimate of the *Probability of not refinancing* over time (on the y-axis) for a given fixation period. The x-axis shows elapsed months since loan origination, and each step down in the KM curve indicates occurrence of the refinancing event. The shaded bands represent approximate pointwise 95% confidence intervals.

Table B3: LPM Robustness Checks

	Dependent variable:				
	Refinancing Decision (1 = Refinanced, 0 = Not)				
	(1)	(2)	(3)	(4)	(5, without Prague)
MoRD	0.0002**	0.0001	0.0002***	0.0001*	0.0002**
	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
expR	0.0009***	0.0009***	0.0009***	0.0009***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(Net_Income)	−0.0014***				−0.0013***
	(0.00007)				(0.00009)
log(Loan_Size)	0.0010***				0.0010***
	(0.00006)				(0.00007)
LSTI		0.00002***			
		(0.000003)			
LTI			0.0003***		
			(0.00002)		
LTV				0.00005***	
				(0.000002)	
Age_Client	0.0011***	0.0011***	0.0011***	0.0011***	0.0011***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Age_Client^2	−0.00002***	−0.00002***	−0.00002***	−0.00002***	−0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Broker_No	−0.0011***	−0.0013***	−0.0012***	−0.0011***	−0.0010***
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Employee_Yes	0.0046***	0.0046***	0.0047***	0.0045***	0.0048***
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Constant	−0.0118***	−0.0150***	−0.0164***	−0.0184***	−0.0178***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Region Controls	YES	YES	YES	YES	YES
Year Controls	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Observations	3,261,928	3,261,928	3,261,928	3,261,928	2,836,445
R^2 (adj.)	0.0035	0.0033	0.0034	0.0035	0.0031
Out-of-Bounds %	9.8%	9.8%	9.8%	9.8%	8.0%

Notes: *p<0.05; **p<0.01; ***p<0.001. Standard errors (in parentheses) are clustered at the loan level. “Out-of-Bounds %” is the fraction of predictions lying outside [0,1].

Figure B5: Survival Curves by Broker Channel



Note: The curves show Kaplan–Meier survival estimates (probability of not refinancing) over the fixation period, split by broker use. A lower curve indicates a higher refinancing hazard. Broker and non-broker curves only diverge meaningfully after 12–24 months, consistent with clawback-based incentives discussed in Section 7.

Table B4: Logit Model Results – Interactions with Broker Channel

	Dependent variable:			
	Refinancing Decision (1 = Refinanced, 0 = Not)			
	(1)	(2, without Prague)	(3)	(4, without Prague)
MoRD	0.057**	0.047*	0.057***	0.052***
	(0.018)	(0.020)	(0.012)	(0.013)
expR	0.235***	0.263***	0.235***	0.256***
	(0.037)	(0.040)	(0.028)	(0.030)
Broker_No	−0.238***	−0.223***	−0.183***	−0.168***
	(0.026)	(0.028)	(0.022)	(0.024)
MoRD×Broker_No	0.007	0.004		
	(0.027)	(0.029)		
expR×Broker_No			−0.084*	−0.077*
			(0.041)	(0.038)
Other covariates[1]	YES	YES	YES	YES
Region controls	YES	YES	YES	YES
Year controls	YES	YES	YES	YES
Bank controls	YES	YES	YES	YES
Observations	3,261,928	2,836,483	3,261,928	2,836,483
Log Likelihood	−82,472	−95,144	−103,915	−89,578
Akaike Inf. Crit.	205,812	178,635	207,911	179,236

[1] Other covariates: log(Net_Income), log(Loan_Size), Age_Client, Age_Client^2, Employee_Yes.
Note: *p<0.05; **p<0.01; ***p<0.001. Columns (1) and (3) are estimated on the full sample, while columns (2) and (4) exclude loans originated in Prague. "MoRD" denotes the mortgage rate differential and "expR" the expected interest-rate change at fixation expiry. "Broker_No" is a dummy for loans not intermediated by a broker. Coefficients are log-odds; standard errors (in parentheses) are clustered at the loan level.

Table B5: Cox Proportional Hazard Models (Collapsed Dataset)

	Dependent variable:						
	Time to Event						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MoRD_avg	1.28***	1.23***	1.25***	1.26***	1.27***		1.26***
	(0.018)	(0.018)	(0.018)	(0.021)	(0.018)		(0.018)
MoRD: -0.5 to 0						2.03***	
						(0.025)	
MoRD: 0 to 0.5						3.55***	
						(0.029)	
MoRD: <0.5						4.03***	
						(0.031)	
expR_avg	14.1***	14.9***	15.1***	17.7***	13.6***	13.7***	
	(0.22)	(0.22)	(0.22)	(0.22)	(0.24)	(0.23)	
expR: -0.5 to 0							3.70***
							(0.089)
expR: 0 to 0.5							3.33***
							(0.092)
expR: <0.5							3.07***
							(0.094)
LSTI 15–20		1.00***					
		(0.024)					
LSTI 20–25		1.03***					
		(0.024)					
LSTI 25–30		1.06***					
		(0.027)					
LSTI 30+		1.02					
		(0.025)					
LTI 1.5–3			1.19***				
			(0.032)				
LTI 3–5			1.22***				
			(0.031)				
LTI 5–6.5			1.28***				
			(0.033)				
LTI 6.5+			1.19***				
			(0.035)				
LTV 50–60				1.15***			
				(0.036)			
LTV 60–70				1.21***			
				(0.031)			
LTV 70–80				2.23***			
				(0.027)			
LTV 80+				0.83***			
				(0.026)			
log(Net_Income)	1.14***	1.23***	1.25***	1.26***	1.16***	1.13***	1.15***
	(0.018)	(0.019)	(0.018)	(0.021)	(0.020)	(0.019)	(0.018)
log(Loan_Size)	1.17***	1.24***	1.17***	1.27***	1.17***	1.24***	1.16***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)
Age_Client	1.27***	1.29***	1.29***	1.26***	1.27***	1.28***	1.27***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age_Client^2	0.99***	0.99***	0.99***	0.99***	0.997***	0.99***	0.99***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.001)
Broker_No	0.88***	0.87***	0.88***	0.87***	0.89***	0.90***	0.88***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Employee_Yes	2.15***	2.08***	2.08***	2.08***	2.46***	2.20***	2.16***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Region, Bank and Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,404	56,404	56,404	56,404	49,067	56,404	56,404
Concordance (Harrell's C)	0.924	0.922	0.923	0.928	0.923	0.931	0.926
Likelihood Ratio Test	57,101	56,791	56,845	59,046	48,928	59,210	57,129
Score (logrank) Test	138,057	137,789	137,831	139,215	119,985	140,133	138,050

Note: *p<0.05; **p<0.01; ***p<0.001. The dependent variable in these Cox regressions is the *time to event* (time until refinancing). The reported coefficients in the table are $\exp(\hat{\beta})$ (hazard ratios). A hazard ratio above 1 means that a one unit increase in the covariate *increases* the hazard (and thus shortens the expected time-to-event), while a hazard ratio below 1 indicates a *decrease* in the hazard. Cluster robust standard errors (in parentheses).

Table B6: Cox Proportional Hazard Models (Stratified)

	Dependent variable:						
	Time to Event						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MoRD	1.127***	1.107***	1.132***	1.103***	1.124***		1.111***
	(0.0134)	(0.0132)	(0.0133)	(0.0135)	(0.0143)		(0.0137)
MoRD: -0.5 to 0						1.086***	
						(0.0267)	
MoRD: 0 to 0.5						1.214***	
						(0.0315)	
MoRD: >0.5						1.341***	
						(0.0359)	
expR	1.218***	1.214***	1.215***	1.220***	1.255***	1.248***	
	(0.0268)	(0.0268)	(0.0268)	(0.0268)	(0.0286)	(0.0267)	
expR: -0.5 to 0							2.263***
							(0.0909)
expR: 0 to 0.5							2.724***
							(0.0923)
expR: >0.5							3.015***
							(0.0920)
LSTI 15–20		1.159***					
		(0.0240)					
LSTI 20–25		1.221***					
		(0.0242)					
LSTI 25–30		1.208***					
		(0.0261)					
LSTI 30+		1.132***					
		(0.0237)					
LTI 1.5–3			1.445***				
			(0.0322)				
LTI 3–5			1.659***				
			(0.0309)				
LTI 5–6.5			1.801***				
			(0.0335)				
LTI 6.5+			1.651***				
			(0.0339)				
LTV 50–60				1.227***			
				(0.0354)			
LTV 60–70				1.348***			
				(0.0314)			
LTV 70–80				1.551***			
				(0.0272)			
LTV 80+				1.619***			
				(0.0264)			
log(Net_Income)	0.743***				0.775***	0.743***	0.745***
	(0.0183)				(0.0205)	(0.0183)	(0.0183)
log(Loan_Size)	1.212***				1.222***	1.212***	1.209***
	(0.0131)				(0.0140)	(0.0131)	(0.0131)
Age_Client	1.576***	1.565***	1.562***	1.558***	1.558***	1.576***	1.575***
	(0.0090)	(0.0090)	(0.0089)	(0.0090)	(0.0097)	(0.0090)	(0.0090)
Age_Client^2	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***	0.994***
	(0.00012)	(0.00012)	(0.00012)	(0.00012)	(0.00013)	(0.00012)	(0.00012)
Observations	2,926,954	2,926,954	2,926,954	2,926,954	2,553,853	2,926,954	2,926,954
Concordance (Harrell's *C*)	0.632	0.628	0.633	0.633	0.626	0.633	0.633
Likelihood Ratio Test	4593	4351	4635	4669	3674	4595	4696
Score (logrank) Test	3118	2894	3149	3174	2548	3119	3207

Note: *p<0.05; **p<0.01; ***p<0.001. Each column corresponds to a stratified Cox PH model with different sets of controls for LSTI, LTI, LTV, or categorized rate differentials. The reported coefficients are exponentiated estimates (hazard ratios). A hazard ratio above 1 implies a higher refinancing hazard (shorter time to event), and a ratio below 1 implies a lower hazard (longer time). All models are stratified by broker usage (`BROKER_NO`), income source (`Employee_YES`), bank code, year, and region (`Region`). Standard errors (in parentheses) are clustered at the loan level.

Table B7: Logit Model Results - Alternative Matching Procedure

	Dependent variable:				
	Refinancing Decision (1 = Refinanced, 0 = Not)				
	(1)	(2)	(3)	(4)	(5, without Prague)
MoRD	0.080***	0.068**	0.120***	0.079***	0.068**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.023)
expR	0.035*	0.017	0.024	0.023	0.029*
	(0.018)	(0.052)	(0.052)	(0.052)	(0.015)
log(Net_Income)	−1.256***				−1.263***
	(0.034)				(0.038)
log(Loan_Size)	0.185***				0.151***
	(0.023)				(0.025)
LSTI		0.003*			
		(0.001)			
LTI			0.084***		
			(0.006)		
LTV				0.009***	
				(0.001)	
Age_Client	0.532***	0.432***	0.439***	0.431***	0.542***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.020)
Age_Client^2	−0.007***	−0.006***	−0.006***	−0.006***	−0.007***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Broker_No	−0.220***	−0.308***	−0.254***	−0.276***	−0.224***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.037)
Employee_Yes	1.109***	1.082***	1.120***	1.064***	1.225***
	(0.055)	(0.055)	(0.055)	(0.055)	(0.067)
Constant	−3.426***	−15.020***	−15.690***	−15.650***	−4.010***
	(0.510)	(0.349)	(0.350)	(0.351)	(0.559)
Region Controls	YES	YES	YES	YES	YES
Year Controls	YES	YES	YES	YES	YES
Bank Controls	YES	YES	YES	YES	YES
Observations	7,160,326	7,160,326	7,160,326	7,160,326	6,178,089
Log Likelihood	−73,267	−74,688	−74,515	−74,551	−61,620
Akaike Inf. Crit.	146,614	149,455	149,108	149,180	123,319

Note: *p<0.05; **p<0.01; ***p<0.001. Each column (1–5) shows a logit specification estimating the probability of refinancing (1 = yes, 0 = no). The main predictors are the mortgage rate differential (MoRD) and the expected rate change (expR), alongside borrower-level covariates. All columns include region, year, and bank fixed effects. Coefficients are log-odds; Standard errors (in parentheses) are clustered at the loan level.

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