The Long Shadows of the Great Inflation: Evidence from Residential Mortgages*

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Abstract

In most countries, the prevailing type of long-term mortgage is variable rate. In the US, 80% of mortgages have fixed rates, which is hard to explain under the standard life-cycle consumption framework. We link this puzzle to the long-lasting effects of the Great Inflation and show that personal experiences of high interest rates affect interest-rate expectations and mortgage choices. Using the Residential Finance Survey, the Survey of Consumer Finances, and mortgage-rate surveys, we estimate a structural discrete-choice model and quantify the welfare implications. Our simulations imply that Baby Boomers overpaid $22bn for fixed-rate mortgages in the late 1980s and 1990s.

Keywords: Financial contracts, household finance, experience effects, behavioral finance, inflation expectations, mortgage choice.

JEL Classifications: D14, D83, D84, D91, E31, G41, G51.

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1 Introduction

Buying a home is the biggest financial decision for many households, with important consequences for lifetime saving and consumption. Most buyers take on significant leverage, entering a financial commitment that commonly stretches over 30 years.

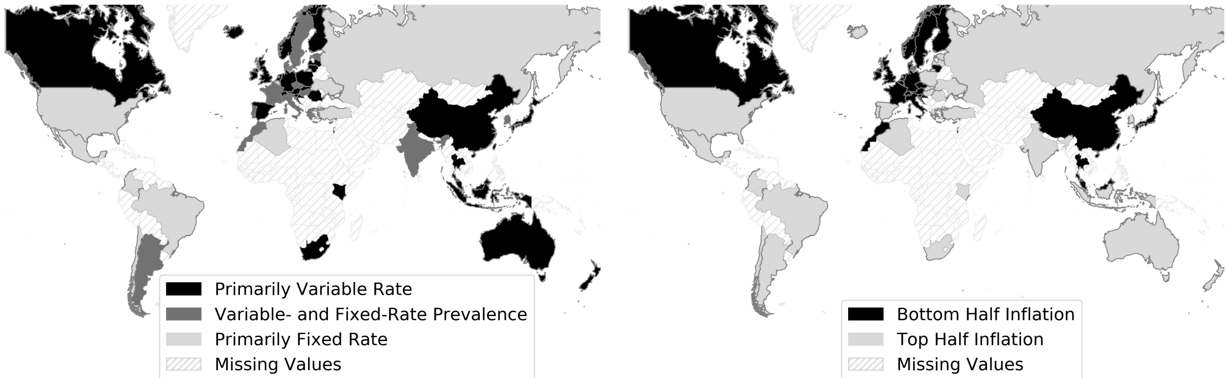
Given their long-term nature, it is not surprising that most markets around the world feature primarily adjustable-rate mortgages (ARMs), as the left map in Figure 1 illustrates. Adjustable (or "variable") rates rise and fall with market interest rates, lowering the risk and cost of financing for the bank, which in turn allows for cheaper mortgage products.

The map also reveals that the US is an exception as fixed-rate mortgages (FRMs) command a market share of 80%. While historical path dependencies from Great-Depression-era housing policies, as well as subsequent regulatory and institutional factors play a role, the FRM's continued dominance is puzzling. It is costly for consumers and, under the standard consumption model, most households, particularly young and mobile ones, are predicted to choose an ARM (Campbell and Cocco 2003; 2015). Our own calculations below confirm that far more households choose FRMs than the standard economic model predicts, especially Baby Boomers in the wake of the Great Inflation. This generation should have taken out 740,000 fewer FRMs in the late 1980s, and 400,000 fewer in the late 1990s. The costs of these deviations are large: Baby Boomers overpaid by about $22 billion. Market characteristics (e. g., payment structure, interest deductability, or rental-market regulation) and demographics (such as life-cycle stages, age, fertility, household size, and mobility) do not suffice to explain the puzzle (cf. Campbell 2013, Guiso and Sodini 2013).

In this paper, we document the role of a different determinant of mortgage choice, namely, prior personal experiences of high inflation and interest rates. Our research hypothesis builds on the notion frequently discussed among practitioners, that the Great Inflation cast "long shadows" that continued to generate fears of rising nominal rates decades later. The idea is that the prolonged exposure to high inflation and high nominal rates in the 1970s and

Figure 1. ARM Prevalence and Historical Inflation Around the World

Panel A. Mortgage Markets Panel B. Historical Median Inflation



Notes. In Panel A, *Primarily Variable Rate* indicates that at least 75% of all mortgages have variable interest rates for the entire duration of the mortgage or after at most five years; *Variable- and Fixed-Rate Prevalence* indicates that at least 25% and less than 75% of all mortgages have variable rates; and *Primarily Fixed Rate* indicates that less than 25% of all mortgages have variable interest. In Panel B, *Bottom Half Inflation* comprises all countries with a median inflation (since 2000) below 2.2%; *Top Half Inflation* includes all countries with a median inflation of at least 2.2%. All data sources for both panels are listed in Appendix B.

1980s generated an aversion to variable-rate borrowing. Internationally, too, high historical inflation appears to predict FRM prevalence, as the right and left map in Figure 1 indicate.

We start by providing some institutional background about the US mortgage market and the rise and fall of ARMs in the 1980s and early 2000s. We then sketch a simple theoretical model relating interest-rate experiences to beliefs about future interest rates and, as a result, mortgage choices. The model illustrates that the structural relationship between experiences and mortgage choices can be estimated with relatively few additional assumptions.

We then operationalize the notion of "long shadows of past inflation" by constructing a measure of experience-based learning that closely resembles the measure in Malmendier and Nagel (2016). Previous work on experience effects (cf. also Malmendier and Steiny 2016) has focused on inflation experiences; but a common criticism is that consumers are unlikely to think about inflation rates when making financing decisions. More plausibly, interest rate fluctuations come to mind. Our study fills the gap by showing how experiences of inflation relate to experiences of nominal interest rates, and how interest-rate experiences in turn affect mortgage choice. (As a robustness check, we also estimate the effect of inflation experiences.) We exploit cross-sectional differences in individuals' personal histories, as well as changes in these cross-sectional differences over time, as the sources of identification.

The empirical analysis relates past interest experiences to FRM-vs-ARM choices. Our goal is to assess the magnitude of the effect of experiences on mortgage contracts and the cohort-specific payoff-implications. To accomplish this, we estimate a discrete-choice model over mortgage alternatives, and we use the structural parameter estimates to quantify the effect of counterfactual interest-rate histories on mortgage choice at the household level.

The estimation faces two challenges. First, we only observe the contract terms households have chosen, not the alternatives they turned down. Second, the sample of households that choose a given product is self-selected. To address these challenges, we turn to a data set that has not been explored in this context, the Census Bureau's Residential Finance Survey (RFS) from 1991 and 2001. The data are unique in that they survey both the household and the mortgage servicer, providing detailed demographic information, mortgage contract terms, and the geographic location of borrowers, allowing us to estimate the fixed and variable rates available to a typical borrower in a given location at a certain point in time.

We use a three-step procedure following Lee (1978) and Brueckner and Follain (1988) to construct the alternative contract terms and account for selection. In Step 1, we estimate a reduced-form model of mortgage choice that only uses *exogenous* variables. The key explanatory variable is Freddie Mac's Primary Mortgage Market Survey (PMMS) rate for standardized FRMs and ARMs to a representative, prime borrower in a Census region-year.

In Step 2, we estimate FRM and ARM mortgage rates for each household, again as a function of the regional (FRM and ARM) survey rates plus households attributes associated with risk characteristics and preferences, including marital status, income, urban versus rural location, and mortgage seniority. The identification of household-specific pairs of mortgage rates is a key contribution of this analysis. Borrowers choosing an FRM likely differ from those choosing an ARM along both observable and unobservable dimensions. Step 2 corrects for the selection bias that arises from estimating over the non-random subsample that chose a given alternative by implementing the semiparametric Newey (2009) series estimator and using the predicted choice probabilities from the first step. To that end, it is critical, in Steps 1 and 2, to rely on mortgage rates that are not afflicted by borrower heterogeneity.

In Step 3, we use the predicted, characteristic-adjusted pairs of mortgage rates for each household to estimate a structural choice model. We find that about one in six households (16%) were close enough to indifference that we can attribute their FRM choice to past exposure to high interest rates. The choice-model estimates indicate that consumers are willing to pay 7–17 bp for every additional percentage point of personally experienced inflation.

We next assess the dollar cost associated with past interest-rate experiences and the resulting higher willingness to pay for FRMs. We simulate how much interest an individual would have paid under standard 30-year FRM or ARM contracts. The present value of excess interest paid (in year-2000 dollars) that is attributable to the inflation-experience coefficient in the structural choice equation amounts to \$8000–\$19,000 in a typical household, depending on the interest-rate adjustments for household risk characteristics and accounting for taxes, typical refinancing behavior, and expected tenure. The estimates imply the potential for significant welfare losses due to the influence of past interest-rate experiences.

We also calculate the *ex-ante* cost by simulating hypothetical interest-rate environments. Monte Carlo simulations calibrated to historical US data indicate that the *ex-ante* expected cost of choosing an FRM that is attributable to individuals' experience-effect coefficient is \$10,400. The FRM is cheaper for these households in only 10% of replications. Gains in replications where average interest rates are high are small compared to losses in replications where average interest rates are low. Hence, choosing an FRM due to personal experiences of high interest rates is expensive in expectation.

The last part of our analysis assesses the underlying mechanism. As proposed in our theoretical model, we find that past interest-rate experiences directly affect future interest-rate *expectations*. Using Survey of Consumer Finances (SCF) data, we show that, in the early survey waves (1989, 1992, etc.), members of younger cohorts were more likely to expect interest rates to rise than members of older cohorts. At that time, younger cohorts also had higher lifetime experiences of interest rates. The relative positions of older and younger cohorts reverse in the mid-2000s, as the memory of the Great Inflation is fading. At that time new, younger households with little or no experience of the Great Inflation enter the sample with lower expectations. This pattern holds for all households, including non-mortgage-holders (renters and outright owners), ruling out ex-post rationalization by FRM borrowers.

We then use experiences as an instrument for beliefs to estimate the relationship between interest-rate beliefs and mortgage choice directly. The household finance literature has long argued that borrowers' heterogeneous interest-rate expectations should strongly affect their contract choices. A key challenge in testing this hypothesis is that non-panel surveys such as the SCF report interest-rate beliefs at the time of the survey, not at the time of the past mortgage choice. This timing discrepancy introduces measurement error into the interest-rate belief variable. We overcome this problem by using experience effects as an instrument for beliefs in a bivariate probit model. We also replicate our reduced-form estimate of the relationship between experiences and mortgage choice in the SCF. The replication across two such different datasets (RFS and SCF) provides strong supporting evidence for our hypothesis.

Our paper contributes to the extensive research on residential mortgage choice and consumer welfare. The theoretical literature establishes that younger borrowers, who are mobile and have rising incomes, and borrowers with stable incomes should prefer an ARM (Brueckner 1986; Alm and Follain 1987; Brueckner 1992). Early empirical work found that borrower characteristics were not major determinants of mortgage choice (Dhillon et al. 1987; Brueckner and Follain 1988; Follain 1990; Peek 1990),[1] but subsequent papers (Sa-Aadu and

[1] Paiella and Pozzolo (2007) replicate this finding for Italy.

Sirmans 1995; Coulibaly and Li 2009; Bergstresser and Beshears 2010) find a stronger role for characteristics such as age, income, and mobility.

Borrowers' interest-rate expectations have long been viewed as important (Brueckner 1986) but difficult to study: "expectation effects must be relegated to the error term in the mortgage choice equation" due to a lack of observability and identification (Brueckner and Follain 1988). We contribute to this discussion by showing how personal experiences of interest rates influence expectations, moving borrowers' heterogeneous expectations out of the error term and into the set of identified explanatory variables.

Conceptually our analysis of expectations builds on the work of Case and Shiller (1988) and Shiller (1999, 2005) as well as an early literature from the time of the Great Inflation that first proposed that the resulting change in inflation expectations might distort housing decisions (see, e. g., Kearl 1979, Baesel and Biger 1980, and Alm and Follain 1984). The more recent literature on non-standard belief formation and mortgage borrowing includes Koijen, Hemert, and Nieuwerburgh (2009), who explain US mortgage choice with an adaptive-expectations "rule of thumb" under which households use only the most recent three years of yield curve data. Bailey et al. (2018, 2019) consider the role of house-price expectations and their non-standard determinants on mortgage and tenure choice.[2]

One issue with adaptive approaches is that they fail in international data and are weaker for different time periods (Badarinza, Campbell, and Ramadorai 2018). The long-term perspective of experience effects helps resolve these discrepancies. While consumers overweight the recent past, earlier experiences exert a long-lasting influence, so beliefs are different across different generations and converge slowly over time. In two countries with identical interest-rate histories but different population age profiles, adaptive expectation would

[2] Armona et al. (2018) show a causal effect of new information on house price belief formation using a randomized survey. Other research on extrapolative expectations and house price dynamics includes Glaeser et al. (2008), Mayer and Sinai (2009), Gelain and Lansing (2014), Granziera and Kozicki (2015), Gao et al. (2017), Glaeser and Nathanson (2017), and Guren (2018). On non-standard expectations and house prices see Piazzesi and Schneider (2009), Case et al. (2012), Favara and Song (2014), Burnside et al. (2016), Suher (2016), Landier et al. (2017), Gao et al. (2018), Kuchler and Zafar (2018), and Nathanson and Zwick (2018).

predict the same FRM share, whereas experience effects predict different FRM shares.[3]

The literature on experience effects shows that personal experiences of macro-finance outcomes have a long-lasting impact on beliefs and choices, often in the context of the stock market (e.g., Kaustia and Knüpfer (2008, 2012), Malmendier and Nagel 2011, Strahilevitz et al. 2011, Knüpfer et al. 2017, Laudenbach et al. 2018) or unemployment (e.g., Oreopoulos et al. 2012, Malmendier and Shen 2015).[4] Most relevant to our study, Malmendier and Nagel (2016) show that personal inflation experiences predict inflation expectations and investment in real estate.[5] Our paper provides the first direct evidence on interest-rate experiences affecting interest-rate beliefs, the missing link in prior work on inflation experiences and mortgage choice. Malmendier and Nagel (2016) also relate mortgage borrowing in the SCF to experienced inflation, though the results on the type of mortgage are weak or insignificant, likely due to data limitations, which we overcome using the RFS. We are the first to present quantitative estimates of the impact of experiences on the FRM–ARM choice ARMs and its payoff consequences. Our cost estimates suggest significant welfare consequences.

2 Institutional and Historical Background

The dominant mortgage in the US is a 30-year, level-payment, self-amortizing, fixed-rate contract. A typical ARM contract also self-amortizes over a long period such as 30 years, but monthly payments vary as the interest rate resets periodically at a prespecified margin over an index, typically the one-year Treasury bill rate or a district cost-of-funds index. ARMs are significantly cheaper than FRMs, particularly during an initial "teaser rate" period.[6]

[3] Other research on behavioral factors in mortgage design and regulation includes Bar-Gill (2008), Ghent (2015), Schlafmann (2016), Atlas et al. (2017), Gathergood and Weber (2017), Gottlieb and Zhang (2018).

[4] Theoretical treatments include Collin-Dufresne, Johannes, and Lochstoer (2016), Malmendier, Pouzo, and Vanasco (2020), and Schraeder (2015).

[5] Past inflation also correlates with homeownership across European countries (Malmendier and Steiny 2016), and influences FOMC members' inflation forecasts and votes (Malmendier et al. 2018).

[6] Fannie Mae ran an advertising campaign in 1984 emphasizing these benefits. One ad showed a picture of a roller coaster with the text, "So far in the 1980's, rising interest rates have pushed the cost of fixed rate mortgages so high that many Americans can't afford them. So, to help lenders lower the initial cost of borrowing to homebuyers, the ARM (Adjustable Rate Mortgage) was developed" ("How to Help the Homebuyer Ride Out the Ups and Downs of Fluctuating Interest Rates." *Wall Street Journal*, 9/21/1984).

Historically, FRMs have not always been the dominant type of mortgage. Prior to the 1930s, the typical mortgage had variable rates and required a large "balloon" or "bullet" payment at maturity. During the Great Depression, many home borrowers defaulted on their mortgages, lacking the income for these one-time payments and unable to refinance (Green and Wachter 2005). In response, Congress established Fannie Mae (1938) and Freddie Mac (1970). Their mandate is to purchase long-term, fixed-rate mortgages from banks, so lenders can shed the interest-rate risk associated with holding these assets to maturity. These policy choices led to the FRM's dominant position for the next 40 years.

In the 1970s, ARMs re-emerged. Rising inflation and interest rates provoked a series of "credit crunches" beginning in 1966 and throughout the 1970s (Bordo and Haubrich 2010). Whenever market interest rates rose above Regulation-Q imposed deposit ceilings, deposits flowed out of the banking sector, and banks contracted their lending (Koch 2015). Savings & loans, the primary suppliers of mortgage credit at the time, were particularly impacted (Mayer 1982). In response, banks lobbied policymakers to allow adjustable-rate mortgages. ARMs were permitted for state-chartered S&Ls in a few Western states in the early 1970s, for federally-chartered S&Ls in 1979, and for all housing lenders in 1982.[7]

After their nationwide reintroduction, ARMs took off. According to the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS), ARMs accounted for 62% of conventional, single-family mortgage originations in 1984,[8] and the head of the US League of Savings Institutions predicted that "There's no way fixed-rate mortgages will survive."[9] But by the end of the 1980s, the ARM share fell below 40% and averaged around 20% over the next two decades. Empirical studies of the rise and fall of ARMs in the 1980s conclude that supply-side factors such as underpricing and demand-side factors such as borrower age,

[7] Miller (1986) provides a detailed history of the legislative and policy debate.

[8] FHFA makes annual share data for all home types available from 1982–2008 and monthly share data from January 1985–October 2008, See Chart 1 in Peek (1990) for earlier monthly data.

[9] Quoted in Schellhardt, Timothy D. and Conte, Christopher "S&Ls Pushing to End Homebuyers' Preference for Fixed-Rate Loans." *Wall Street Journal*, July 1, 1983, p. 17.

income, and mobility played only a minor role.[10] In his 1990 Presidential Address to the American Real Estate and Urban Economics Association, James Follain argued that it was "strongly related to movements in the level of interest rates and the FRM–ARM rate spread."

ARMs regained market share during the housing boom of the 2000s. ARMs and "hybrid" ARMs (whose rates are initially fixed for more than a year) peaked at 40% of originations in June 2004.[11] Following the crash, ARM originations fell to such low levels that MIRS stopped tracking them in November 2008. According to the Mortgage Bankers Association, ARMs accounted for less than 10% of mortgage applications in 2009–2021 (cf. Urban Institute 2022).

In summary, the continued dominance of fixed-rate financing in the US after 1970s-era deregulation was by no means guaranteed. The historical background points to a role for the macroeconomic environment influencing attitudes towards ARMs.

3 Theory, Measurement, and Data

We introduce a simple model relating past experiences of interest rates to interest-rate expectations and mortgage demand. The model guides our measurement of experiences effects and the quantification of welfare implications.

3.1 Theory

Consider the choice between a fixed-rate mortgage F and an adjustable-rate mortgage A. Suppose household n's expected indirect utility, $U_{n,j}$, over mortgage type $j \in \{F, A\}$ is

$$U_{n,j} = \beta_{0,j} + \beta_{\iota,j}\iota_{n,t} + \beta_{R,j}Rate_{n,j} + \beta'_{x,j}x_n^B + \upsilon_{n,j}\,. \tag{1}$$

[10] Cf. Dhillon et al. 1987; Brueckner and Follain 1988; Peek 1990.

[11] Some observers link the increase in ARMs to the expansion in subprime credit supply, blaming the ensuing default and foreclosure crisis on "exploding ARMs" whose monthly payments skyrocketed after the initial teaser-rate period. Foote et al. (2012) document the rise of this theory around 2007 and convincingly dispute it ("Fact 1: Resets of adjustable-rate mortgages did not cause the foreclosure crisis"); see also Posey and Yavas (2001), Mayer et al. (2009), and Cocco (2013). Fifteen years on, the theory continues to circulate in popular discussions of the financial crisis: see "Adjustable-Rate Mortgages are Back, but Aren't Like You Remember" by Orla McCaffrey, *The Wall Street Journal*, May 29, 2022.

where $\iota_{n,t}$ is n's forecast of future interest rates based on time t information; $Rate_{n,j}$ is the current FRM or ARM rate that a lender offers individual n; x_n^B are other observable borrower characteristics that affect contract choice; and $\upsilon_{n,j}$ are unobserved factors.[12] Let $x'_{n,j} = (Rate_{n,j}, x_n^{B'})$ and $x'_n = (Rate_{n,F}, Rate_{n,A}, x_n^{B'})$. n chooses F if $U_{n,F} - U_{n,A} > 0$, with

$$\begin{aligned} U_{n,F} - U_{n,A} &= (\beta_{0,F} - \beta_{0,A}) + (\beta_{\iota,F} - \beta_{\iota,A})\iota_{n,t} + \beta_{R,F} Rate_{n,F} - \beta_{R,A} Rate_{n,A} \\ &\quad + (\beta_{x,F} - \beta_{x,A})' x_n^B + (\upsilon_{n,F} - \upsilon_{n,A}) \\ &= \delta_0 + \delta_1 \iota_{n,t} + \delta'_x x_n + u_n \,. \end{aligned} \tag{2}$$

Interest-rate expectations $\iota_{n,t}$ matter because households that expect higher interest rates discount future payments by more, so they estimate the present value of fixed-repayment obligations to be smaller. By contrast, the present value of adjustable-rate obligations is unaffected because the forecast of higher future ARM payments and the use of a higher discount rate offset one another. Hence, borrowers who forecast higher future interest rates perceive the FRM to be relatively cheaper and have a greater inclination to choose an FRM over an ARM. That is, $\delta_1 \equiv \beta_{\iota,F} - \beta_{\iota,A} > 0$ in (2).

Against the null hypothesis of rational expectations, we hypothesize that household n's personal experiences of past interest rates, accumulated as of time t, $i^e_{n,t}$, affects their time-t forecast of future nominal interest rates as in the following equation:

$$\iota_{n,t} = \alpha_{0,t} + \alpha_1 i^e_{n,t} + \xi_{n,t} \,. \tag{3}$$

The rational expectations baseline is represented by year fixed effects $\alpha_{0,t}$. A positive coefficient α_1 indicates that past interest-rate experiences $i^e_{n,t}$ raise n's individual expectations relative to this baseline. The forecast error term $\xi_{n,t}$ represents other idiosyncratic factors.

We obtain an estimating equation by plugging (3) into (2),

$$\begin{aligned} U_{n,F} - U_{n,A} &= (\delta_0 + \delta_1 \alpha_{0,t}) + \delta_1 \alpha_1 i^e_{n,t} + \delta'_x x_n + (u_{n,t} + \delta_1 \xi_{n,t}) \\ &= \delta_{0,t} + \delta_{ie} i^e_{n,t} + \delta'_x x_n + u^*_{n,t} \,. \end{aligned} \tag{4}$$

[12] Households sign a mortgage only once, at time t, so we omit time subscripts in $Rate_{n,j}$ and $U_{n,j}$.

Our hypothesis is that the structural coefficients δ_1 and α_1 are positive, so the coefficient on interest-rate experiences in our estimating equation is also positive, $\delta_{ie} \equiv \delta_1 \alpha_1 > 0$.

3.2 Measurement

Our measure of past interest-rate experiences builds on prior theoretical and empirical research on experience effects, which has shown that personal experiences of inflation and other macro-finance variables predict beliefs about future realizations of the same variable. Individuals appear to weight past lifetime realizations with roughly linearly-declining weights when forming beliefs (Malmendier and Nagel 2011, 2016). We thus calculate the lifetime experiences of realized interest rates i as of year t for an individual born in year s as:

$$i^e_{s,t} \equiv \sum_{k=0}^{t-s} \frac{t-s-k}{\sum_{j=0}^{t-s}(t-s-j)} \cdot i_{t-k}\,. \tag{5}$$

This formula places the highest weight on the most recent observation ($k = 0$), zero weight on the year of birth ($k = t - s$), and connects these endpoints linearly. Lifetime experiences of other variables, such as inflation, are defined correspondingly.

We apply this formula to the annual averages of monthly market yields of 90-day Treasury bills since 1934. For 1920–33, when T-bills were not issued regularly, we use the average yield on 3–6 month Treasury notes and certificates.[13] For individuals born prior to 1920, we rescale the weights based on available years.[14] We focus on short-term rates because ARM payments are typically indexed to a short-term rate such as the one-year Treasury yield, so this is what households should forecast in equation (3) and compare to the current FRM rate. Our main results are similar if we use long-term government bond yields.

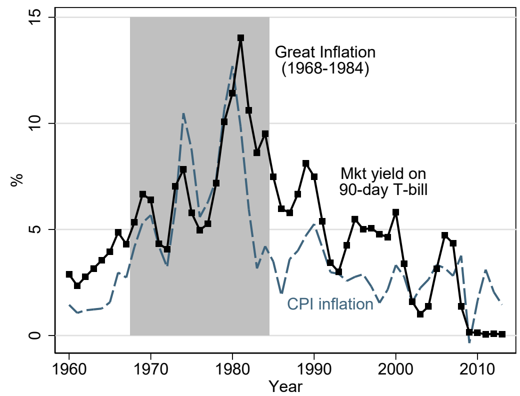
Figure 2 illustrates the historical time series of interest rates and resulting evolution of $i^e_{s,t}$. Panel A plots average inflation (dashed line) and interest rates (filled squares) from 1960–2013. Both series soared to double-digit levels during the Great Inflation (1968–1984),

[13] Treasury bills are pure discount bonds whose yield is determined at auction; Treasury notes and certificates were coupon bonds offered at a fixed price (Garbade 2008). See Appendix A for data sources.

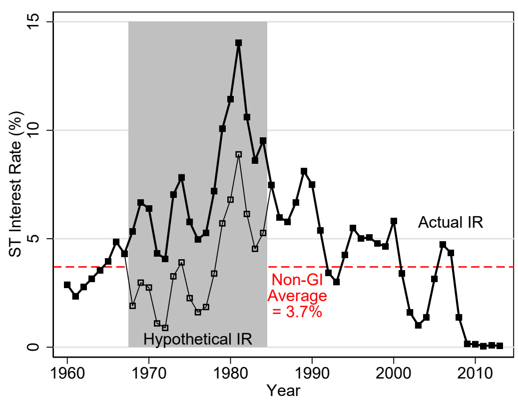
[14] E.g., the lifetime experiences of interest rates as of 1922 for an individual born in 1915 is $5/18 \cdot i_{1920} + 6/18 \cdot i_{1921} + 7/18 \cdot i_{1922}$. The weights would be $(5/28, 6/28, 7/28)$ if 1915-1919 data were also available.

Figure 2. The Great Inflation, Interest Rates, and Interest Rate Experiences

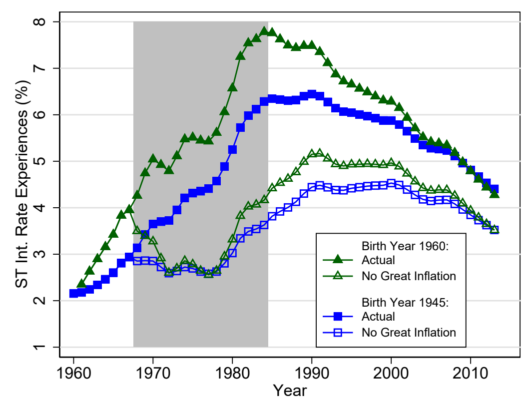
Panel A. Inflation and Interest Rate, 1960–2013



Panel B. Hypothetical Interest Rate



Panel C. Interest-Rate Experiences



Notes. Panel A plots annual CPI inflation from BLS (dashed line) and the 90-day T-bill market yield (solid boxes). In Panel B, Hypothetical IR (hollow boxes) is a location-scale transformation of actual 1968–84 interest rates (mean 7.60%, SD 2.77%) to the 1960–2013 mean and SD, excluding 1968–84 (mean 3.72% and SD 2.22%): $i_t^H := (i_t - 0.0760)/0.0277 \times 0.0222 + 0.0372$. In Panel C, solid symbols show lifetime interest-rate experiences as in (5). Hollow symbols show the same, but using hypothetical interest rates during 1968–84.

shaded in gray.[15] Panel B shows a hypothetical "No-Great-Inflation" interest-rate path, representing what might have happened if inflation had not taken off and the Volcker Fed had not raised interest rates in response (hollow squares). Panel C shows the resulting lifetime weighted-average experiences under both actual and hypothetical interest rates, separately for two representative households, an "older" one born 1945, and a "younger" one born 1960.

The comparison of these lines provides two main insights. First, young borrowers are particularly affected by interest-rate shocks: Their experiences shoot up more steeply, reflecting

[15] Our methodology for dating the Great Inflation is inspired by Scrimgeour (2008); see Appendix C.

their shorter personal histories. Even in the hypothetical "No Great Inflation" scenario, the younger cohort's lifetime average increases 50 bp more than that of the older cohort after the second oil price shock in 1979. In reality, the difference exceeded 150 bp in 1982. However, by the late 1990s the lifetime experiences of both cohorts are fairly similar in both scenarios.

Second, after the Great Inflation, lifetime averages remain higher than under the hypothetical scenario for many years, well into the 2000s. In other words, interest rate shocks have a double effect: an immediate effect on the cross-section and a long-lasting effect on the level. Our empirical analysis quantifies the implications of these two effects for mortgage choice.

3.3 Data

We rely on two main sources of data: the Residential Finance Survey (RFS) and the Survey of Consumer Finances (SCF). The RFS has been conducted by the Census Bureau the year after every decennial Census from 1950 to 2000. It is much larger than other sources of mortgage data: its homeowner survey interviewed 24,000 households in 1991, and nearly 17,000 in 2001. The RFS is unique in combining two cross-referenced surveys, one of households and one of their mortgage servicers. The household arm provides demographic and income data, and the lender arm the terms of any outstanding loans secured by the property. The sample is drawn from the previous year's Census roster of properties, so it misses some newly-constructed housing. The survey oversamples multi-unit properties, particularly rental properties with 5+ units, but is otherwise representative of the outstanding mortgages in the preceding year. Property locations are reported at the state level for 12 large states (CA, FL, TX, and NY in both survey years, plus eight additional states in 2001 only) and at the Census region level otherwise. In our final sample, we observe the state-level location for 44% of mortgages.

Our analysis utilizes all outstanding mortgages linked to owner-occupied 1–4 unit properties from the 1991 and 2001 waves.[16] We do not observe mortgages that were repaid in full or

[16] Including second and vacation homes, as the public-use 1991 RFS does not let us filter these out.

defaulted upon prior to the survey year. In the case of refinancing, we observe only the new mortgage. To approximate flow data, we restrict the sample to mortgages taken out no more than six years prior to the survey (1985–1991 and 1995–2001). Mortgagor age at origination is a key input for calculating interest-rate experiences. We use the age of the self-identified primary owner if the household has multiple members, and keep only borrowers aged 25 to 74 at origination as in Malmendier and Nagel (2016).

Some variables such as income and loan amount are coded to interval means to preserve respondent anonymity, and interest rates are left- and right-censored. We explicitly account for censored dependent variables in our estimation procedure. Also, origination years in the 1991 survey are reported as 1985–86, 1987–88, and 1989–91 intervals. To calculate interest rate experiences, we assume origination at the beginning of the interval, so as to exclude future rates that some borrowers had not yet experienced. When determining conforming versus jumbo status, we use the largest conforming loan limit in each time period, since loans tend to cluster just below this amount. All details are in Appendix A.

Table 1 reports the summary statistics for the RFS data, separately for FRMs, ARMs, and balloon mortgages, the three types that are reported consistently across survey waves. Balloon mortgages offer lower monthly payments that are not fully amortizing. A "balloon" payment is due after 7–10 years, which borrowers typically pay by refinancing into a new mortgage for the remaining 20–23 years. Assuming the borrower qualifies for a new loan, a balloon mortgage acts like a cross between an FRM and an ARM: the interest rate resets once over 30 years, as opposed to never (FRM) or annually (ARM) (MacDonald and Holloway 1996). Only 4.8% are balloon mortgages, so we will mostly focus on fixed- versus variable-rate contracts. FRMs are somewhat smaller than ARMs and significantly more expensive.

Borrower, property, and other loan characteristics are in the lower parts of Table 1. ARM holders tend to have higher income, are less likely to be first-time homeowners, and are more likely to take out a "jumbo" loan (above the conforming loan limit) than FRM holders. There is no significant age difference between FRM and ARM borrowers, contrary to the prediction of standard theory, but consistent with the mixed findings in previous empirical work. Lifetime interest rate experiences are very similar for the typical FRM and ARM borrower (6.39% versus 6.37%). Rather than contradicting our theory, this reflects across-year variation in prices: ARMs were most popular in the 1980s, when the average FRM–ARM spread was steeper, and interest rate experiences were higher due to the recent Great Inflation. The relationship between experiences and mortgage choice matches our theory when we condition on year fixed effects.

We confirm and extend our results using Survey of Consumer Finances data. The triennial SCF run by the Federal Reserve Board gathers detailed, household-level income and balance-sheet data. We use the SCF to test directly whether past experiences of interest rates affect households' beliefs about future interest rates, using survey question X302, "Five years from now, do you think interest rates will be higher, lower, or about the same as today?" The question was introduced with the redesign of the SCF in 1989, but discontinued after 2013. We thus confine our analysis to the nine survey waves between 1989 and 2013.

The typical SCF survey wave is much smaller than the RFS, around 4000 households in 1989–2007, and 6000 starting in 2010. Since the SCF oversamples the wealthiest households, the use of sampling weights is important.[17] For example, in the 2013 SCF, unweighted average household income is $710k, versus $84k when weighted to adjust for heterogeneous sampling and response probabilities. Also, due to the sensitive nature of the questions, data is missing in a non-random fashion. Board statisticians use multiple imputation both to fill in missing values and to replace non-missing values that might disclose respondents' identities. The public-use data contains five simulated "implicates" (imputation-replicates) per household. We adjust standard errors for multiple imputation using the standard Rubin (1987) formulas.

[17] For more details on SCF weight construction, see Kennickell and Woodburn (1999).

The top panel of Table 2 shows weighted summary statistics for all respondents between the ages of 25 and 74, including non-mortgage holders. The mean respondent is 47 years old, has a household income of $88k per year (median of $58k), and a net worth of $477k (median of $101k) in constant 2013 dollars. Two-thirds of respondents are home owners, and two-thirds of owners have a mortgage, reducing the sample from 36,266 to 16,824 households. 86% of mortgages have fixed rates, and only 6% are jumbo loans. More than a quarter of mortgages (28%) are "non-conventional," meaning that they carry VA or FHA insurance or guarantees.

The bottom panel of Table 2 restricts the data to "new" mortgages, originated in the 1989–2013 survey years. This restriction approximates flow data over a longer period than the RFS, albeit with fewer observations: 3263 new mortgages of 3025 households (9% of the original sample). Similar to the RFS, FRM holders are close in age to ARM holders, but have lower income, less net worth, and smaller loans that are less likely to be jumbo.

In both panels, we report the fraction of respondents expecting higher or lower interest rates as well as the net fraction answering "higher" minus the fraction answering "lower." On net, borrowers choosing FRMs are 10 pp more likely to expect higher future interest rates than those choosing ARMs, 68% versus 58%. The difference is driven by FRM holders expecting rising interest rates, and not by ARM holders expecting falling interest rates. Borrowers choosing FRMs have lower lifetime experiences of both interest rates and inflation. The difference are larger than in the RFS because the SCF includes a longer slice of the 2000s, when the FRM share rose and memories of the Great Inflation receive the lowest weight in equation (5). This points to the importance of performing a within-year calculation.

Overall, the borrower, property, and other loan characteristics in the RFS go significantly beyond the level of detail available in the SCF data, whereas the SCF provides better time-series coverage. When variables are comparable, comparisons of FRM to ARM holders yield similar conclusions. While we focus on the larger RFS data, the mortgage choice results replicate across both data sets, and the SCF allows us to pin down the beliefs mechanism.

We supplement these main datasets with Freddie Mac's Primary Mortgage Market Survey (PMMS), a weekly survey of average FRM and ARM rates from a representative nationwide sample of mortgage originators, broken out into five regions. Lenders provide quotes for first-lien, prime, conventional, conforming, home purchase mortgages with an 80% LTV and a 30-year term, for both FRMs and 1/1 ARMs, and the initial "teaser" rate and the margin over the one-year Treasury rate (after the loan resets) for ARMs. The PMMS provides a picture of mortgage rates charged to the same high-quality borrower, across products and over time.[18] We match annual averages of the weekly PMMS data to borrower locations in the RFS using the Freddie Mac region containing the borrower's state.[19]

4 Interest Rate Experiences and Mortgage Choice

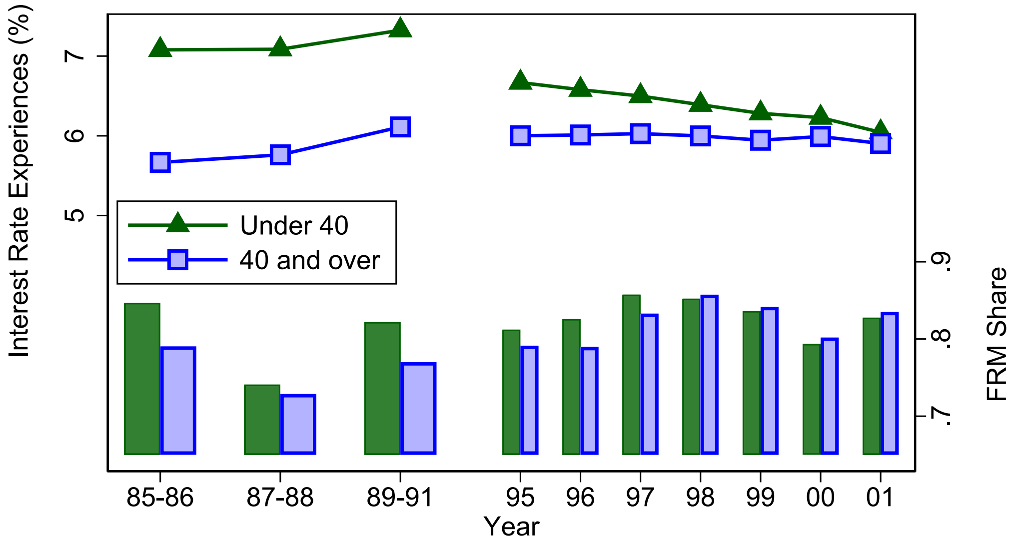
We start with a graphical illustration of the two main implications of our research hypothesis: (i) mortgage borrowers who have been exposed to higher historical interest rates are more likely to choose FRMs; and (ii) younger cohorts respond more strongly to recent interest-rate realizations. The first implication reflects that households with higher past interest-rate experiences expect higher future interest rates (equation (3)), and hence estimate the present value of FRM payments to be smaller relative to ARM payments. The second implication reflects the recency bias embedded in experience-based learning (equation (5)). Younger individuals with shorter lifetime histories overweight recent experiences more than those with longer histories, and thus respond more strongly to recent interest rate realizations.

Figure 3 illustrates that both predictions hold in the aggregate. Splitting the RFS sample at the median age of 40, we plot the FRM share and interest-rate experiences of "younger"

[18] Another popular interest-rate series, the FHFA's Monthly Interest Rate Survey (MIRS) draws instead from *actual* mortgages and reflects changes in the pool of borrowers across products and over time. Appendix D shows that the PMMS tracks the slope of the nominal Treasury yield curve much more closely.

[19] If the borrower's state is not reported, we construct a Census region average by re-weighting the PMMS data from the five Freddie Mac regions to the four Census regions using 1990 Census housing units by state.

Figure 3. FRM Share and Interest Rate Experiences by Age Group



Notes. Data from the 1991 & 2001 RFS and BLS CPI. The 1991 RFS reports origination years in two- or three-year intervals. Left (right) bars show FRM share for households with head under 40 (40 and over).

and "older" borrowers in 1985–1991 and 1995–2001. In the late 1980s, younger cohorts with shorter personal histories were more affected by the Great Inflation and more likely to choose fixed rates than older cohorts. In the late 1990s and early 2000s, the interest-rate experiences of younger and older cohorts converged—memories of the Great Inflation faded for older cohorts, while (new) younger cohorts had no personal memory of it—and so did mortgage choices. The remainder of this section tests for this pattern formally.

4.1 Estimation Methodology

To estimate equation (4), $U_{n,F} - U_{n,A} = \delta_{0,t} + \delta_{ie} i^e_{n,t} + \delta'_x x_n + u^*_{n,t}$,[20] we expand the equation with $\delta'_x x_n = \beta_{R,F} Rate_{n,t,F} - \beta_{R,A} Rate_{n,t,A} + \delta'_x x^B_n$. The probability that $U_{n,F} \geq U_{n,A}$ is

$$\Pr(U_{n,F} \geq U_{n,A}) = \Pr(-u^*_{n,F} \leq \delta_{0,t,F} + \delta_{ie,F} i^e_{n,t} + \beta_{R,F} Rate_{n,t,F} - \beta_{R,A} Rate_{n,t,A} + \delta'_{x,F} x^B_n), \quad (6)$$

where $Rate_{n,t,F}$ and $Rate_{n,t,A}$ are the fixed and variable rates offered to household n in year t, and vector x^B_n includes borrower characteristics relevant for mortgage choice. Optimal mortgage choice depends on income volatility, risk aversion, and liquidity (Alm and Follain 1984, 1987; Campbell and Cocco 2003) as well as expected future income and mobility

[20] Full details are in Appendix E.

(Brueckner 1986, 1992). Thus, we control for the log of current income; age and age squared, capturing the nonlinear life-cycle profiles of income and mobility; and joint-owner status, which may proxy for lower income volatility, or (if the owners are married) greater liquidity constraints and risk aversion due to the presence of children. The purchase of discount points should indicate a longer expected tenure (Dunn and Spatt 1988; Stanton and Wallace 1998);[21] and non-conventional loans are given to riskier borrowers (greater income volatility). In the SCF, we proxy for liquidity constraints via log net worth, but in the RFS analysis this is in the error term, $u^*_{n,j}$. We also include a dummy for rural counties, as borrowers' income paths and mobility might differ systematically across rural and urban areas.

Equation (6) shows that we can estimate separate mortgage rate coefficients ($\beta_{R,F}$, $\beta_{R,A}$) for each mortgage type; but for variables that do not differ across alternatives, including macroeconomic factors and borrower characteristics, only differences in coefficients, $\delta_{\cdot,F} \coloneqq \beta_{\cdot,F} - \beta_{\cdot,A}$, are identified. Positive (negative) values of $\delta_{\cdot,F}$ increase (decrease) the probability of choosing the FRM. Maximum-likelihood estimation proceeds by making a distributional assumption on the error difference $u^*_{n,F} = v^*_{n,F} - v^*_{n,A}$.[22]

The explanatory variable of interest is n's lifetime experience of nominal interest rates at the time of the choice situation, $i^e_{n,t}$. Interest-rate experiences depend on birth year and age: different cohorts have different lifetime histories at the same age. Repeated cross-sectional data lets us identify both life-cycle (age) effects and experience effects. We hypothesize that households with higher interest-rate experiences expect higher future interest rates, and thus higher utility from the FRM mortgage alternative: $\delta_{ie,F} > 0$.

For interpretation and hypothesis testing, the year fixed effects $\delta_{0,t,F}$ are essential. They capture all aspects of the economic environment at a given time and all information that is common to all households. Thus, a borrower's lifetime interest-rate experiences should not matter for the rational-expectations forecast. That is, *conditional on year fixed effects*, the

[21] We use discount points to back out borrowers' expectations about their future mobility in Appendix E.4.
[22] Or on the joint vector of error differences $(u^*_{n,1}, \ldots, u^*_{n,J-1})$ for $J > 2$ alternatives. See Appendix E.

standard rational framework predicts $\delta_{ie,F} = 0$.

The main hurdle to estimating the structural-choice equation (6) is that the data only reports the rate of the mortgage chosen, not the entire menus. We use the three-step procedure of Lee (1978) and Brueckner and Follain (1988) to impute the missing rates and correct for selection bias.[23] First, we predict the rate offered to household n choosing mortgage j as

$$Rate_{n,j} = \gamma_{0,j} + \gamma_{R,j} PMMSRate_{r,t,j} + z_n' \gamma_j + \zeta_{n,j} \, . \tag{7}$$

The Freddie Mac survey rate $PMMSRate_{r,t,j}$ represents the price charged to a high-quality borrower in the same year t and Census region r as borrower n; and z_n are borrower and loan characteristics that proxy for risk: log income, first-time homeowner status (proxy for a shorter credit history), marital status (proxy for lower income volatility), rural location, non-conventional status, loan size, mortgage refinancing, whether it is a second (junior-lien) mortgage, jumbo status,[24] and discount points paid, which directly lower the household's mortgage rate. Equation (7) is estimated separately for each mortgage type j.

Plugging (7) into (6), we obtain a *reduced-form* choice model. Letting $\tilde{z}$ represent the elements of z that are not also in x^B:

$$\begin{aligned} \Pr(U_{n,F} - U_{n,A} \geq 0) = \Pr(&-\tilde{u}^*_{n,F} \leq \tilde{\delta}_{0,t,F} + \delta_{ie,F} i^e_{n,t} \\ &+ \tilde{\beta}_{R,F} PMMSRate_{r,t,F} - \tilde{\beta}_{R,A} PMMSRate_{r,t,A} + \tilde{z}_n' \tilde{\gamma}_F + \tilde{\delta}'_{x,F} x^B_n) \, . \end{aligned} \tag{8}$$

This replaces the pair of half-missing household-level rates $(Rate_{n,t,F}, Rate_{n,t,A})$ with the regional Freddie Mac survey rates $(PMMSRate_{r,t,F}, PMMSRate_{r,t,A})$, which do not depend on household characteristics and are always observed for both alternatives. Moreover, while some reduced-form coefficients differ from their structural analogues (indicated by tildes), the reduced-form choice equation (8) and the structural equation (6) contain the same coefficient $\delta_{ie,F}$ on interest-rate experiences.

Our three-step procedure is as follows. In the first step, we estimate the reduced-form

[23] Lee (1978) confronted a similar problem when estimating the wages of union versus non-union jobs, and Brueckner and Follain (1988) first applied Lee's methodology to a mortgage-choice setting.

[24] Jumbo status reflects supply-side factors due to the difficulty lenders face reselling these loans during periods of financial distress (Fuster and Vickery 2015).

choice model (8), where choices depend on region- and time-specific FRM and ARM rates from the PMMS. In the second step, we estimate two mortgage pricing equations (7), where the household's actual rates depend on the region- and time-specific PMMS rates plus household characteristics that adjust for risk. We correct for selection bias using the predicted choice probabilities from step 1. In the third step, we estimate the structural choice model (6), using the household-level menu of selection-corrected predicted rates from step 2.

We modify the second step vis-à-vis Brueckner and Follain (1988) to reflect the specifics of our data and recent econometric advances. First, we use censored least absolute deviations (CLAD, Powell 1984) rather than OLS, because households' mortgage rates are top coded in the RFS. Second, we correct for selection bias using a semiparametric selection correction (SPSC) estimator proposed by Newey (2009), which generalizes the model of Heckman (1979). Identification of the SPSC model relies on two technical conditions (discussed in Appendix E) and a cross-equation exclusion restriction: $Rate_{n,t,j}$ is a risk-adjusted markup over the PMMS rate for the same product j only. E.g., the ARM survey rate does not directly influence a household's FRM rate, but it does influence the probability that the household will choose an FRM or ARM via (8). This gives us exogenous variation in the first-step choice probabilities that we use to correct for selection bias in the second step.

Finally, predicting interest rates requires an estimate of the rate intercept $\gamma_{0,j}$ in (7). Since the SPSC control function absorbs the intercept, we follow the suggestion of Heckman (1990) and calculate it as the median difference between observed mortgage rates and their fitted values, excluding the correction bias function, for households with choice probabilities close to 1—intuitively, those observations suffering from the least selection bias.

4.2 Choice Model Estimates

We begin our analysis by estimating the reduced-form mortgage choice model. The RFS provides data for three types of mortgages: FRMs, ARMs, and balloon mortgages. A balloon mortgage may be viewed as an ARM that resets once, rather than once per year, so it carries less interest-rate risk than an ARM but more than an FRM. Our theory implies that individuals who have lived through periods of higher interest rates substitute away from both ARMs and balloon mortgages. To incorporate three alternatives into the analysis, we use a multinomial logit model (McFadden 1974) with the ARM as the base category. The rest of the methodology of the previous section easily generalizes; see Appendix E for full details.

Table 3 presents the reduced-form estimates. In columns 1–2, we restrict the latent-utility coefficients on the FRM rate and the ARM initial rate from (8) to be the same: $\tilde{\beta}_{R,A} = \tilde{\beta}_{R,F}$, so households only pay attention to the FRM–ARM rate spread. The negative estimate $\hat{\tilde{\beta}}_R = -0.480$ in column 1 indicates that individuals are more likely to choose an ARM when the spread is higher and an FRM when the spread is lower.

Each "alternative-specific" panel reports latent-utility coefficient estimates for that alternative. We estimate a significant, positive coefficient of $\hat{\delta}_{ie,F} = 0.189$ for the effect of interest-rate experiences on the FRM alternative. The positive estimate indicates that individuals who have lived through periods of high nominal rates are more likely to choose an FRM, relative to the baseline ARM. In the bottom panel, the corresponding coefficient estimates for the balloon alternative relative to the baseline ARM, $\delta_{\cdot,B} \equiv \beta_{\cdot,B} - \beta_{\cdot,A}$, is negative and marginally significant. Together, the two $\delta_{ie,j}$ estimates indicate that the balloon and ARM shares fall, and the FRM share rises, as interest-rate experiences rise.[25] When we impose the restriction $\beta_{ie,Balloon} = \beta_{ie,ARM}$, the coefficient on i^e in the FRM panel becomes even larger and highly significant (column 2, $p < 0.01$). Viewing the balloon as an ARM with a one-time interest rate reset, borrowers who have lived through periods of high interest rates are significantly less likely to choose variable-rate products and strongly prefer FRMs.

We assess the economic magnitude of the estimated effects by calculating the additional interest individuals would be willing to pay (WTP) for an FRM, if their lifetime interest-

[25] The negative estimate of $\delta_{ie,B}$ indicates that the balloon share falls more quickly than the baseline ARM share. This is perhaps surprising, as balloons carry less nominal interest-rate risk than ARMs. On the other hand, periodic ARM resets may be capped, whereas the balloon refinancing "reset" is not.

rate experience were 1 pp higher. Formally, we take the total derivative of utility in (4) with respect to $i^e_{n,t}$ and $Rate_{n,t,F}$ (after expanding with $\delta'_x x_n = \beta_{R,F} Rate_{n,t,F} - \beta_{R,A} Rate_{n,t,A} + \delta'_x x^B_n$) and set it equal to zero: $d(U_{n,F} - U_{n,A}) = \delta_{ie} \partial i^e_{n,t} + \beta_{R,F} \partial Rate_{n,t,F} = 0$. We obtain:

$$WTP := \left. \frac{\partial Rate_{n,F}}{\partial i^e_{n,t}} \right|_{d\Delta U_n = 0} = -\frac{\delta_{ie}}{\beta_{R,F}} \,. \tag{9}$$

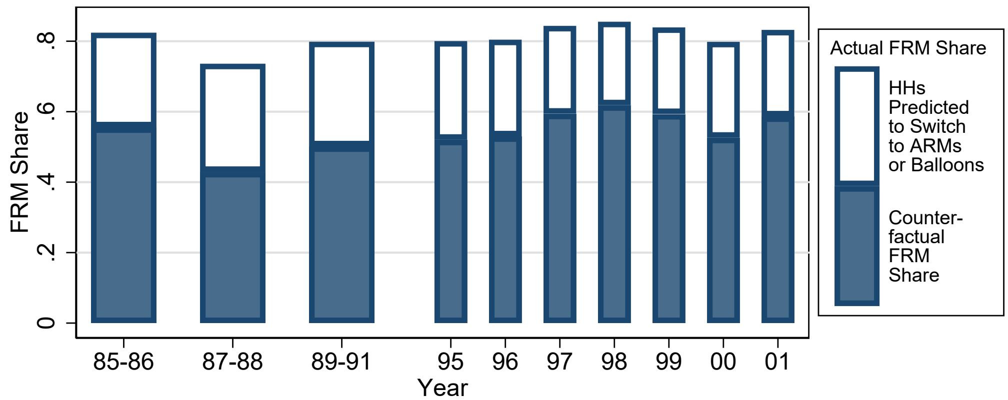
The column 2 estimates imply that individuals are willing to pay $-0.260/(-0.483) = 0.538$ pp in FRM–ARM spread per additional pp of i^e. To put this in perspective, the Great Inflation raised personal experiences of interest rates by 3 pp for younger households in the mid-1980s (cf. Figure 2). These borrowers would be willing to pay an additional 1.5 pp.

In columns 3 to 5, we allow the price coefficients on the FRM and the ARM initial rates to differ. Previous studies either fail to reject the null that these coefficients are the same (Nothaft and Wang 1992) or find that the FRM rate coefficient is smaller in magnitude (Sa-Aadu and Sirmans 1995). We estimate that the FRM rate coefficient is significantly larger in magnitude. That is, the initial ARM rate carries less weight over the lifetime of the mortgage than the known FRM rate. In column 4, we add controls for additional borrower and mortgage characteristics that may affect mortgage choice, and in column 5, we omit the balloon alternative and estimate a binomial choice model between FRMs and ARMs.

Under all specifications, personal experiences of higher interest rates predict a significant increase in the probability of choosing fixed-rate contracts. For example, using the estimates in column 3, individuals are willing to pay $0.256/3.56 = 0.072$ pp more in the FRM rate for every additional percentage point of i^e. This WTP is smaller than in columns 1–2 because we are dividing by a larger FRM rate coefficient. Since all specifications include origination-year fixed effects, this effect is above and beyond the market's full-information interest-rate forecast; rational individuals should place zero additional weight on personal experiences.

To visualize the economic impact of the experience effect on aggregate mortgage choice, Figure 4 shows the fraction of households predicted to switch to an ARM or balloon mortgage if they were not influenced by personal experiences $i^e_{n,t}$. We estimate counterfactual

Figure 4. Actual and Counterfactual FRM Shares



Notes. Data from the 1991 and 2001 RFS. The 1991 RFS reports origination years in two- or three-year intervals. The counterfactual FRM share is based on estimates from Table 3, column 4, with coefficient on interest rate experiences set to zero.

probabilities using the estimates from Table 3, column 4 (with the full set of controls) but replace the $\hat{\delta}_{ie,FRM}$ estimate with 0. We then aggregate these probabilities to calculate hypothetical product shares for each origination year. The predicted mortgage shares add the year fixed effect coefficients back in, so adjust for all aspects of the economic environment and all publicly-available information, including the full history of past interest rates.

The counterfactual FRM share (shaded in) is 31 pp lower in 1987–88 (43% vs. 74%) and 30 pp lower in 1989–91 (50% vs. 80%) if borrowers ignored $i^e_{n,t}$. The effect of interest-rate experiences slowly diminishes as memory of the Great Inflation recedes: by 2001, the counterfactual FRM share is still 25 pp lower than the actual share, 58% rather than 83%. This reflects the double effect of interest rate shocks seen in Figure 2: they raise the level of lifetime experiences for many years and have a long-lasting influence on borrower behavior.

In the second step, we impute the interest rates of the non-chosen alternatives. Since the balloon alternative occupies such a small market share, we restrict our attention to the FRM and ARM alternatives. To correct for selection bias, we run a selection model using the same explanatory variables as in the last column of Table 3, except for the origination-year fixed effects, which we will include in the third step. To adjust standard errors for the presence of predicted regressors (the choice probabilities), we bootstrap the procedure 200 times.

Table 4 shows censored LAD and ordered-logit estimates of FRM and ARM pricing equations (7), without and with semiparametric selection correction (SPSC) in columns 1, 3, 5 versus 2, 4, 6. (See Appendix E for details on the selection bias control function.)

Columns 1 and 2 show that many of the FRM rate coefficients are affected by the inclusion of the SPSC terms. The biggest difference is in the coefficient on non-conventional status, from an insignificant +0.2 bp to a highly significant −182 bp. Non-conventional mortgages are offered to riskier borrowers, who would pay more if not for the FHA or VA insurance or guarantee. Selection correction also has noticeable effects on the coefficients for the PMMS rate, joint owners (i.e. marital status), rural location, loan size/CLL, and jumbo status.

To formally test for the presence of selection bias, we calculate a Hausman (1978)-style test statistic. The test statistic is a quadratic form, $(\hat{\Gamma}_{SC} - \hat{\Gamma}_{noSC})'\hat{V}^{-1}(\hat{\Gamma}_{SC} - \hat{\Gamma}_{noSC})$, where $\hat{\Gamma}$ represents all the coefficient estimates in (7) except the constant, and $\hat{V}$ is a bootstrapped estimate of the variance of their difference between the models with and without selection correction. The sample test statistic value reported at the bottom of column 2, 46.6, is well above the 5% critical value of 19.7 for the $\chi^2_{(11)}$ distribution, providing strong evidence in favor of selection bias in the FRM pricing equation. We also report the mean value of the SPSC control function in the bottom row (see equation (A.7) in Appendix E). Negative "average selection bias" indicates that individuals who chose an FRM received an interest rate about 178 basis points lower than would be expected given their observable characteristics $Z_{n,j}$. In contrast with Brueckner and Follain (1988), who found no evidence of selection bias in their data, borrower selection has a significant impact on FRM pricing.

In the ARM initial-rate pricing equations in columns 3 and 4, the selection bias is directionally similar, but the changes are smaller and the Hausman-style test fails to reject no selection bias. Somewhat surprisingly, average selection bias is positive for those choosing an ARM, but it is much smaller in magnitude than for the FRM subsample.

For the ARM-margin estimation, we discretize the distribution of margins into ten intervals using the 1991 RFS reporting categories and estimate an ordered logit.[26] This method implicitly accounts for censoring and predicts households' choice probabilities for each interval. We multiply the probabilities by the 2001 RFS medians within each interval to calculate an expected, risk-adjusted margin for each household. Columns 5 and 6 report the marginal effects of each covariate on the expected value of the margin, averaged over all observations.

We estimate a negative relation between the PMMS initial ARM rate and households' expected margins, suggesting that lenders backload interest when teaser rates are low. We estimate a big effect of non-conventional status on ARM margins. Most other covariates have small and insignificant marginal effects, and we again fail to reject the null of no selection.

With these estimation results in hand we turn to the structural choice model. Table 5 presents the estimates of (6), where the dependent variable indicates an FRM choice. The explanatory variables *Rate Offered* and *Margin Offered* are the predicted values from Table 4 for both the chosen and non-chosen alternatives. We adjust standard errors for the first- and second-step estimation by bootstrapping the entire three-step procedure 200 times.

A comparison of columns 1, 3, and 5 with columns 2, 4, and 6 reveals the importance of selection correction in the second-stage estimation of (7). Without selection correction, the price coefficients are insignificant and often have the wrong sign. With selection correction, the signs indicate the expected downward-sloping demand curve: a higher FRM (ARM) rate is associated with a lower (higher) probability of choosing the FRM. The experience-effect estimates, by contrast, are unaffected by selection correction.

Columns 1 and 2 include only the FRM and the initial ARM rate predictions from step 2. Columns 3 and 4 add the risk-adjusted ARM margins to the estimation. With the selection correction, the estimated coefficients on the FRM and ARM initial rates are very similar

[26] We switch to an ordered-logit estimator since, in unreported specifications, all CLAD estimates other than the junior mortgage dummy are precisely estimated zeros, and the junior mortgage dummy carries the same significant coefficient of +25 bp both without and with the selection correction. That is, CLAD fails to adjust ARM margins for household risk, possibly because over half of all sample ARMs carry the same margin, 2.75 pp. The ten categories are $[0, 100)$, 100, $(100, 200)$, 200, ..., $(400, 500)$, $[500, \infty)$.

to column 2, while the coefficient on the ARM margin becomes small and insignificant. In columns 5 and 6, we also control for non-conventional status. Consistent with the theory that borrowers with riskier income streams prefer FRMs (Campbell and Cocco 2003), the estimated coefficient is positive and significant. Moreover, all rate coefficients now take the correct signs in both columns (and all are significant in column 6).[27] Similar to many previous studies, we find that borrower characteristics are not a major determinant of mortgage choice: age, income, and joint-owner status are individually and jointly insignificant.

Turning to the variable of interest, we find that borrowers with personal histories of higher interest rates are more likely to choose an FRM, regardless of how we predict mortgage prices or the set of controls. The estimated WTP is 17–27 bp per pp of interest-rate experiences in the structural model, compared to 4–7 bp in the comparable reduced-form model estimates.

Supply-Side Constraints. Our baseline analysis assumes that all borrowers choose between FRM and ARM contracts. However, some might only qualify for an ARM due to constraints on the ratio of debt service over income, and others might not be offered an ARM due to income risk. Appendix H shows that our results are even stronger for borrowers with low loan-to-income ratios, who most likely had "free choice" between mortgage types.

Experiences of Inflation and Other Interest Rates. We also test whether we can relate mortgage choice to other lifetime experiences. In Appendix I we use equation (5) to calculate lifetime experiences of inflation, real interest rates, long-term interest rates, and the Treasury yield curve slope. Since variation in nominal interest rates might be driven by inflation via a long-run Fisher (1930) effect or backward-looking monetary policy (Taylor 1993), whether individuals learn from nominal interest rate experiences, inflation experiences, or real interest-rate experiences is not theoretically distinct. Nor do we have much power empirically to distinguish among the mechanisms, since the main source of variation for nominal interest rates and inflation is the Great Inflation period (cf. Figure 2).

[27] We fail to reject the null hypothesis that all three price coefficients are equal in magnitude in col. 6.

Nevertheless, we investigate whether these alternative specifications generate similar results.

We re-estimate the reduced-form mortgage choice model (8), replacing $i^e_{n,t}$ with $\pi^e_{n,t}$ and $r^e_{n,t} \coloneqq \pi^e_{n,t} - i^e_{n,t}$. As expected, the results are very similar in terms of sign, statistical significance, and economic magnitude (WTP). The results using real interest rate experiences are not statistically different from zero.

We also consider specifications using households' experiences of long-term government bond yields, $i^e_{LT,n,t}$, and the slope of the Treasury yield curve, $YC^e_{n,t} \coloneqq i^e_{LT,n,t} - i^e_{n,t}$. Since long-term bond yields reflect market expectations of future short-term yields plus a term premium, $i^e_{LT,n,t}$ should be a noisy proxy for the theoretically-relevant $i^e_{n,t}$. The estimated coefficient is very similar indeed, though estimated less precisely and just short of conventional cutoffs for statistical significance. Finally, we find that borrowers with steeper yield curve experiences are less likely to choose an FRM, consistent with them estimating a higher term premium and expecting a larger FRM–ARM payment differential (Koijen et al. 2009).

5 Financial Costs and Welfare Implications

How costly are these effects for consumers? Whether experience effects induce a welfare loss *ex post* depends on realized interest rates; whether they induce a welfare loss *ex ante* depends on the full distribution of possible interest rates that could have occurred.

In this section, we provide estimates over varying horizons and under varying assumptions about repayment, mobility, and historical as well as simulated interest rates.

5.1 Measurement: Welfare-Relevant Treatment Effect

To assess financial costs, we need to (1) identify whose choice is affected by experience effects, and (2) calculate whether their experienced-induced choice was costly or beneficial.

As for step (1), the relevant subset are households who chose an FRM only because experience-based learning figured into their choice function and who would not have chosen the FRM under a full-information Bayesian forecast of future nominal interest rates. To identify this subset of "switchers," we define each household's *switching probability* as

$$h_n = \Pr(n \text{ chooses FRM} \mid \delta_{ie} = \eth) - \Pr(n \text{ chooses FRM} \mid \delta_{ie} = 0)\,. \tag{10}$$

where ð indicates the true population value of δ_{ie}. We obtain an estimator of h_n by comparing choice probabilities when the coefficient on interest-rate experiences is as estimated in (6) or (8) versus set to 0, leaving all other estimated coefficients the same. For example, if a household's "true" probability of choosing an FRM is 90% using $\delta_{ie} = \hat{\delta}_{ie}$ and the counterfactual probability is 70% using $\delta_{ie} = 0$, then for every 100 observationally-equivalent households, we expect 70 to choose an FRM no matter what, 10 to choose an ARM no matter what, and 20 to switch from FRM to ARM if they ignore their personal interest-rate experiences.

As for step (2), the historical PMMS data show that the FRM–ARM initial rate spread is always positive, so individuals with short horizons benefit from the ARM's low teaser rate, but over longer horizons the resets could make the ARM more expensive. For example, an individual taking out an FRM in 1993 would lock in a nominal rate of 7.31%. An individual taking out a 1/1 ARM with no reset caps and a 2.75 margin over the one-year Treasury rate would pay only 4.58% in 1993, but 8.06% in 1994, 8.70% in 1995, etc. Resets would keep the subsequent ARM rate above the 1993 FRM rate every year until 2001.

We simulate the monthly payments of each household for a 30-year self-amortizing FRM and an ARM, paid on time (no late penalties or prepayments) and originated on January 1,[28] under three interest-rate scenarios. In Scenario 1, we assign everyone the Freddie Mac PMMS mortgage rate, varying only by region and year. This sidesteps the issue of estimating individual-level pricing equations, but may over- or understate the financial costs as it does not adjust for household risk characteristics. In Scenario 2, we use the selection-corrected CLAD estimation to predict risk-adjusted FRM rates and ARM teasers (Table 4, columns 2 and 4), while ARM margins are adjusted for seniority only. In Scenario 3, we use ordered

[28] We randomly assign the 1991 RFS households to a year in their origination interval (1985–86; 1987–88; or 1989–91). Results are similar if we assign all households to the first or last interval year.

logit to predict ARM margins based upon household characteristics (Table 4, column 6).

ARM borrowers receive the teaser rate for one year, after which annual resets are based on the appropriate margin over the average value of a 1-year constant maturity Treasury for that year: plus 2.75 pp (Scenario 1), plus 2.75 pp if first-lien and 3.00 pp if second- or third-lien (Scenario 2), or plus a risk-adjusted margin from the selection-corrected ordered logit estimation results (Scenario 3). Our Scenario 1 reset margin of 2.75 pp from the PMMS is very close to the average ARM margin in the RFS, confirming its validity (see Table 1).

We discount the simulated paths of interest payments back to the origination year using a nominal discount rate of 8%, and we assume that households deduct mortgage interest at a marginal income tax rate of 25%. Let $Y_{n,1}$ be the after-tax, PDV of interest payments under the FRM offered to household n, and $Y_{n,0}$ under the ARM alternative, $\Delta Y_n \equiv Y_{n,1} - Y_{n,0}$ is the *ex post* financial cost of choosing the FRM (if positive) or benefit (if negative) for n.

Our summary measure, the *Welfare-Relevant Treatment Effect (WRTE)*, is the sum of the simulated ΔY_n across all households, weighted with their estimated switching probabilities:

$$\widehat{WRTE} \coloneqq \sum_{n=1}^{N} \Delta \hat{y}_n \left(\frac{\hat{h}_n}{\sum_n \hat{h}_n} \right). \tag{11}$$

This WRTE is equivalent to the expected difference between FRM and ARM payments for households that chose an FRM because of their interest-rate experiences (cf. Appendix E.2).[29]

5.2 Costs over Different Holding Periods

Table 6 shows the resulting estimates. The row "% switching households" indicates that about one in six households (16%) were close enough to indifference that we can attribute their FRM choice to long-lasting effects of their lifetime interest-rate experiences.

Using these switching probabilities as weights in (11), we first calculate the WRTE as of the RFS survey year (1991 or 2001), shown in the left column labeled "Survey Year" in each panel. It estimates the extra cost that switching households have incurred by originating an

[29] We choose the name "WRTE" in reference to Heckman and Vytlacil (2007), who formulate a "policy-relevant treatment effect" (PRTE) using the same weighted average.

FRM rather than ARM up to six years prior and continuing to hold it through the survey year. Using unadjusted PMMS rates to simulate the payments (Scenario 1, top panel), we estimate that the average switching household paid \$2200 in extra interest (up to the survey year), in after-tax, present value terms. This estimate rises to \$8100 if we adjust the FRM and the initial ARM rate for household risk characteristics (Scenario 2, middle panel), or \$7700 if we additionally adjust the ARM margin (Scenario 3, bottom panel).

The survey-year estimates provide a lower bound on the true WRTE. To estimate the expected financial cost of experience-induced choices over the entire 30-year lifetime of the mortgage, we need to model households' refinancing behavior and mobility.

We report estimates for three types of refinancing behavior. First, we assume that households never refinance and hold the mortgage until maturity. This is a worst-case scenario for an FRM in a falling interest-rate environment. Second, we assume that households refinance the FRM "optimally," whenever the interest rate on a new FRM is sufficiently below its current FRM rate, using the square-root rule derived by Agarwal et al. (2013). We predict the refinanced FRM rate using the selection-corrected estimates in Table 4 and updated PMMS rates for each year, holding all household characteristics fixed except the refi dummy. Third, we calculate costs based on "expected refinancing" following Andersen et al. (2015).[30] For every year t after origination, we estimate the probability that the household holds a mortgage last refinanced s years after origination. We integrate over these probabilities for all $s \leq t$ to calculate the household's *expected* FRM payments, across the entire distribution of possible time-t interest rates. This provides an intermediate case between no and optimal refinancing. See Appendix E.3 for further details.

Table 6 shows the cost for all three refinancing assumptions. In scenario 1 (PMMS

[30] Andersen et al. (2015) describe the probability a household refinances in a given period as a function of the interest rate differential. An extensive literature documents that mortgagors often refinance too early, before the rate differential has crossed the optimal threshold, or too late, months or years after the differential has crossed the threshold. See also Green and Shoven (1986), Stanton (1995), Green and LaCour-Little (1999), Bennett et al. (2000), Agarwal et al. (2015), Bajo and Barbi (2015), and Keys et al. (2016).

rates), the WRTE triples between 5 and 15 years, from \$5,200 to \$16,600 if households never refinance. Households pay only \$9,800 in extra interest over 15 years if they refinance as "Expected," and \$7,900 if refinancing is "Optimal." Risk-adjusted rates (Scenario 2) and margins (Scenario 3) produce significantly larger estimates at every holding period; e.g., after 15 years, from \$22,800 if households refinance optimally to \$34,200 if they never refinance.

To generate bottom-line numbers for all three scenarios, we calculate each household's expected tenure. We convert five-year non-mover rates from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) into one-year moving probabilities and fit them to a fourth-order polynomial function of age. (See Appendix E.4 .) We assume that moving events are exogenous and unanticipated by the household. Upon moving, the household sells the house and the stream of mortgage payments stops.

The resulting differences between FRM and ARM interest payments, reported in the final column of Table 6 ("E[tenure|age]"), resemble the 10-year holding estimates, For example, under expected refinancing, we estimate a cost of \$7700, \$19,100, and \$18,000 in Scenarios 1, 2, and 3. Our results are robust to estimating expected tenure via the purchase of discount points (Section E.4), which allow borrowers to pay upfront in exchange for a lower future interest rate and which tend to reveal private information about their expected tenure (Dunn and Spatt 1988). By comparison, our WTP estimates imply an expected 30-year cost of \$5000–\$12,000 in PDV.[31] In summary, for most switching households in our sample, taking out an FRM was likely a very costly mistake *ex post*.

5.3 Different Interest-Rate Environments

The *ex post* estimates rely on the actual realization of inflation and interest rates. To estimate the *ex ante* value of choosing an FRM over an ARM, we re-simulate interest payments for switching households under other environments.

[31] We use a WTP range of 7–17 bp per pp of lifetime interest-rate experiences. For an average mortgage of \$100k, this amounts to \$70–\$170 per year, or \$790–\$1900 over 30 years (discounting at 8%) per pp of i^e, times the average experienced interest rate of 6.4 pp among FRM holders (cf. Table 1).

Historical Environments. First, we consider prior historical inflation and term structures. We choose a rising and a falling interest-rate environment: 1972, as the Great Inflation took off; and 1981, the year that short-term interest rates peaked. We assume that households are identical, including their lifetime inflation and interest-rate experiences, except that they are facing the interest-rate schedule of 1972 or 1981 (and subsequent years).[32] That is, the only component of equation (11) that we change for this thought experiment is the simulated interest payments $\Delta\hat{y}_n$. We use Scenario 3 estimates.

In the rising interest-rate environment, the WRTE is *negative*, indicating that households who choose an FRM over an ARM due to their interest-rate experiences pay *less*. The average switching household is better off by \$7700 under optimal refinancing, or \$6100 under expected refinancing. This economic environment is a best-case scenario for FRMs.

By contrast, in the falling interest-rate environment, FRM choice can be very costly—even if a household refinances close to optimally. We estimate that the average switching household would pay \$24,000 more over its expected lifetime if they refinance optimally, \$25,000 if they refinance as expected and \$53,000 if they never refinance.

This exercise illustrates that, historically, there are plausible scenarios when the experience-induced choice of an FRM paid off, though it was rarely in the money during the Great Moderation. Hypothetical best-case payoffs are 60–70% less than our empirical cost estimates, whereas the hypothetical worst-case loss is 40% more than our estimates.

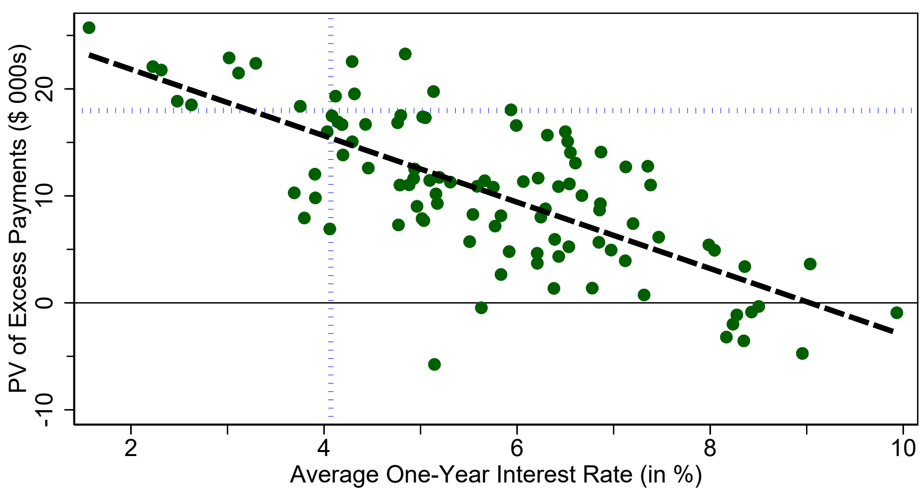
Simulated Interest-Rate Environments. To take the *ex ante* analysis a step further, we run a Monte Carlo simulation of $\Delta\hat{y}_n$ over a wider range of interest-rate environments. In each replication, we draw 30 years of serially-independent real interest rates and AR(1) inflation rates, which we use to calculate the term structure of nominal interest rates and mortgage rates using the Expectations Hypothesis with constant term and risk premia. We plug the simulated national mortgage rates in place of the PMMS rates into our selection-

[32] As the ARM was not available nationwide until 1982, we impute the survey rate by assuming that it would have taken its average value over the 1-year constant-maturity Treasury rate of 1.5 pp.

corrected equation estimates from Table 4 to predict a set of FRM and ARM rates for each household under Scenario 3. We then simulate households' interest payments under both contracts and calculate the WRTE by (11) using the age-based mobility metric. We repeat the process 100 times to obtain a set of 100 different interest-rate environments, mortgage rate paths, and WRTE realizations. See Appendix F for full details and parametrization.

The simulation results in Table 7 show that choosing an FRM due to personal interest-rate experiences is costly *ex ante*. In expectation, the WRTE is \$13,200 under no refinancing, \$10,400 under expected refinancing, and \$8,900 under optimal refinancing. The FRM is more costly in about 90% of replications, regardless of refinancing behavior. This is despite the simulated FRM–ARM rate spread being nearly symmetric around zero: the baseline FRM rate path is only 5 bp higher than the baseline ARM rate path on average (over all 30 years, including the initial teaser rate in year 1 and the rate resets in years 2–30).

Figure 5. Average Interest Rates and WRTEs in Monte Carlo Simulation



Notes. The horizontal axis is the average one-year nominal interest rate and the vertical axis is the WRTE in a replication. Each point is a replication, and thick dashed line is OLS regression line across all 100 replications. Horizontal and vertical crossing lines indicate average values of market yield on US Treasuries at one-year constant maturity over 1986–2013 and WRTE from Table 6. Calculations based on Scenario 3 estimates, expected refinancing behavior, and age-based mobility.

Figure 5 plots the simulated WRTEs against average one-year interest rates in each of the 100 replications, using our age-based mobility metric and expected refinancing. We observe a strong inverse correlation between average interest rates and the *ex post* cost of a fixed-rate mortgage. Univariate linear regression, shown by the thick dashed line, indicates that every additional pp of average interest over the 30-year simulation reduces the expected cost of the FRM by \$3105 (robust s.e. 234) for switching households. Short-term interest rates must average at least 9% for the FRM to be *ex post* beneficial in expectation. Such persistently high interest-rate environments are rare, both in the simulation and in actual US data.

Finally, the figure shows that conditions and outcomes in the 1990s and 2000s are not an extreme outlier. The thin vertical and horizontal crossing lines indicate average one-year Treasury rates over 1986–2013 and the actual WRTE in our data. With the onset of the Great Moderation, interest rates fell to 4.1%, about one standard deviation below their calibrated long-run average of 5.8%. The actual WRTE of \$18,000 is very close to the predicted, simulated value given by the regression line of \$15,400 (s.e. 619).

The bottom line is that, for households who choose an FRM because of personal experiences, it is costly on average, rarely pays out, and when it does the payout is small.

6 Interest Rate Expectations

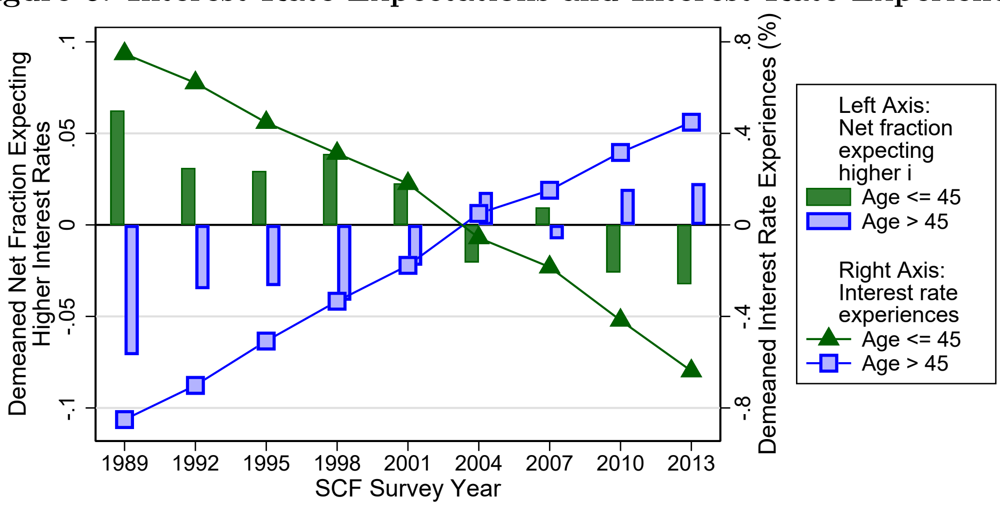
We conclude by considering the mechanism linking interest-rate experiences to mortgage choice. The behavior modeled in equation (4) could reflect either preferences or beliefs. Prior research supports a beliefs channel: high inflation experiences raise inflation expectations (Malmendier and Nagel 2016). Here, we show that interest-rate experiences affect interest-rate expectations (equation (3)), which in turn influence mortgage choice (equation (2)).

6.1 Interest Rate Experiences and Expectations

To test for a beliefs channel we use the SCF question: "Five years from now, do you think interest rates will be higher, lower, or about the same as today?" While the question is coarse compared to more modern surveys such as the New York Fed's Survey of Consumer Expectations (launched in 2013), its wording is similar to the question used for many years in Michigan's Survey of Consumers. It is also more suitable to the mortgage choice decision in that it elicits beliefs over a longer forecast horizon (five years rather than one year).

For each survey wave between 1989 and 2013, and separately for each cohort, we calculate the net fraction of respondents expecting interest rates to rise as the fraction answering "higher" minus the fraction answering "lower." We then relate this fraction to the personal interest-rate experiences of the same households over their lifetimes so far.

Figure 6. Interest-Rate Expectations and Interest Rate Experiences



Notes. Values shown are cohort deviations from survey-year mean (average across implicates).

Figure 6 illustrates the survey responses graphically, separating cohorts above and below the median sample age. The graph shows each group's deviation from the overall survey-year mean. We see that younger cohorts (dark green) were more likely to expect interest rates to rise than older cohorts (light blue) during the early SCF years. This relationship reverses in the mid-2000s, when younger households start to have less lower than older ones.

The timing of this reversal in expectations coincides almost exactly with the cross-sectional differences in interest-rate experiences, calculated as in (5). The graph shows that the younger cohorts (triangles) experienced up to 1.5 pp higher interest rates than that the older cohorts (squares) during the early survey waves, but the relative position switches in the mid-2000s. This reversal happens as new, younger households who did not live through the Great Inflation enter the sample, and the households who did experience the Great Inflation age and become older households. Moreover, the memory of the Great Inflation among older cohorts is fading (i.e., is weighted less).

We confirm the visual pattern by formally estimating equation (3). In Table 8, we use three measures of expectations: the net fraction expecting higher rates as in Figure 6 (columns 1 and 2); an indicator for respondents expecting interest rates to fall (columns 3 and 4); and an indicator for respondents expecting rates to rise (columns 5 and 6). We estimate both a linear probability model (LPM), where the coefficients directly represent marginal effects, and an ordered or binomial probit model. Our research hypothesis predicts coefficient α_1 to be positive in columns 1, 2, 5, and 6; and negative in 3 and 4.

The results confirm that past interest-rate experiences exert a powerful influence on expectations for all measures and estimation methods. Under the LPM, 1 pp higher experienced interest rates predict that a respondent is 6.9 pp more likely to expect higher interest rates on net (col. 1, $p < 0.01$). Columns 3–6 show that higher interest-rate experiences shift the entire distribution of beliefs to the right. Respondents are 2.0 pp less likely to expect rates to fall (col. 3, $p < 0.01$) and 4.9 pp more like to expect rates to rise (col. 5, $p < 0.01$). Since the coefficients in columns 1, 3, and 5 are additive, we can decompose the total effect: $0.049/0.069 \approx 70\%$ of the column 1 effect is driven by more households expecting rising interest rates and $0.020/0.069 \approx 30\%$ by fewer households expecting falling rates.

Crucially, the link between interest-rates experiences and expectations holds not only for mortgage holders, but all 36,264 households in the SCF. In unreported results, we have verified the result among the 19,439 households who *do not have a mortgage* (i.e., who rent or own their home outright). The subsample estimates are very similar to the full sample estimate. This alleviates any concern about FRM holders engaging in *ex-post* rationalization and reporting that they expect higher future interest rates to justify their mortgage choice.

6.2 Interest Rate Expectations and Mortgage Choice

The final step is the structural link from interest expectations to mortgage choice (equation (2)). Jointly estimating equations (2) and (3) requires some auxiliary assumptions about the data-generating processes.

Real-world nominal interest rates are persistent, either because inflation is serially correlated (in 1960–2013, the autocorrelation parameter on log CPI inflation was 0.8), or real interest rates are serially correlated, or both. We assume a stationary AR(1) process:

$$i_t = (\mu + \rho) + \phi(i_{t-1} - \mu - \rho) + \epsilon_{i,t}\,,\ 0 \leq \phi < 1\,, \tag{12}$$

where μ is mean inflation and ρ is the mean real interest rate.[33]

We model the idiosyncratic component of interest-rate forecast ξ from (3), i. e., the "forecast error" that is not related to past interest-rate experiences, as an AR(1) process:

$$\xi_{n,t+1} = \varphi \xi_{n,t} + \nu_{n,t+1}\,,\ 0 \leq \varphi < 1\,. \tag{13}$$

Completing the specification of the DGPs, we assume that the errors in (2), (3), (12) and (13) are all mean zero; that the interest-rate innovations ϵ and the forecast innovations ν in (12) and (13) are unpredictable white noise; that the structural model errors in (2) and (3) are contemporaneously orthogonal; and that the regressors in (2) and (3) are pre-determined (a weaker, time-series version of exogeneity). Letting Ω_{t-1} denote all time $t-1$ information:

$$\mathbb{E}[u_{n,t}] = 0\,,\ \mathbb{E}[\nu_{n,t} \mid \Omega_{t-1}] = 0\,, \mathbb{E}[\epsilon_t \mid \Omega_{t-1}] = 0\,; \tag{14}$$

$$\mathbb{E}[u_{n,t}\xi_{n,t}] = 0\,; \tag{15}$$

$$\text{and } \mathbb{E}[(i_t, i_{t-1}, \ldots)'\xi_{n,t}] = 0\,,\ \mathbb{E}[(\iota_{n,t}, x'_n)'u_{n,t}] = 0\,. \tag{16}$$

Note that (14) implies mean-zero forecast errors (by inverting (13), $\mathbb{E}[\xi] = (1-\varphi(L))^{-1}\mathbb{E}[\nu] = 0$), and (15)-(16) imply that $u_{n,t}$ is orthogonal to $i^e_{n,t}$ (because u is orthogonal to all other components of (3)). Under these assumptions, (2) and (3) can be estimated consistently by single-equation methods: OLS, logit, probit, etc. We will refer to these as "OLS-like" estimators, since identification relies on the OLS-like orthogonality conditions (16).

So far this is all standard. However, the structure of our data introduces a timing

[33] All results follow through if we model the inflation and one-year real interest-rate processes as in our Monte Carlo simulation in Section 5.3, but this approach avoids introducing unnecessary extra notation.

discrepancy: the SCF reports interest-rates beliefs at the time of the survey, not at the time the mortgage was taken out. That is, instead of observing $\iota_{n,t}$ from the time of the mortgage choice, we only observe an *ex post* interest rate forecast $\iota_{n,t+1}$. This introduces an endogenous regressor problem: the *ex post* interest rate forecast incorporates extra, time $t+1$ information that may be correlated with the time-t mortgage choice error term u_t, so OLS-like estimators are inconsistent.

To derive the asymptotic bias in the mortgage-choice estimation with mismeasured interest rate beliefs , we express $\iota_{n,t+1}$ recursively as

$$\iota_{n,t+1} = \iota_{n,t} + \Delta\iota_{n,t+1}, \tag{17}$$

$$\text{where } \Delta\iota_{n,t+1} = \alpha_1 \Delta i^e_{n,t+1} + (\varphi - 1)\xi_{n,t} + \nu_{t+1}\,, \tag{18}$$

with Δ the first-difference operator, following from (3) and (13). Plugging (17) into (2) gives us a feasible second-stage mortgage choice regression:

$$U_{n,FRM} - U_{n,ARM} = \delta_0 + \delta_1 \iota_{n,t+1} + x_n' \delta_x + \underbrace{(u_{n,t} - \delta_1 \Delta\iota_{n,t+1})}_{u^*_{n,t}}. \tag{19}$$

The composite error $u^*_{n,t}$ is the structural error $u_{n,t}$ minus "measurement error" $\delta_1 \Delta\iota_{n,t+1}$.[34]

We compare (19) to (2) from an errors-in-variables perspective. If the interest-rate forecast ι were a random walk, then $\Delta\iota$ would be classical measurement error, and OLS-like estimators would be attenuated. To see this, observe that the *ex-post* forecast $\iota_{n,t+1}$ is positively correlated with the measurement error term $\Delta\iota_{n,t+1}$ by (17), and this latter term has a negative coefficient in (19), so $\iota_{n,t+1}$ is negatively correlated with the composite error term u^*. We derive in Appendix G that this reasoning also holds in our non-classical setting.

In the classical setting, we could use interest-rate experiences at the time of the mortgage choice, $i^e_{n,t}$, as an instrument for interest-rate beliefs at the same time, $\iota_{n,t}$, and the resulting IV-like estimator would be consistent. However, we derive in Appendix G that, due to

[34] Similarly, plugging (17) into (3) would give us a feasible first-stage regression equation of *ex post* interest rate expectations on *ex-ante* interest-rate experiences. However, we observe and can use *ex post* interest-rate experiences as the regressor, so this is not a problem. We show in Appendix G that the OLS estimator otherwise would be attenuated toward zero.

the serial correlation of ι, IV-like estimators are also inconsistent, and that any instrument satisfying the relevance condition fails to satisfy the exogeneity condition: Unlike random walks, serially-correlated processes are mean reverting. Therefore, an instrument that is positively correlated with an individual's time-t interest rate forecast must be negatively correlated with the subsequent change in their forecast, so it cannot be exogenous. Since $\Delta\iota$ has a negative coefficient in (19), such an instrument will be *positively* correlated with the composite error term u^*. Hence, IV-like estimators are *amplified* rather than attenuated.

We utilize that the OLS- and IV-like estimators $\hat{\delta}_{1,OLS}$ and $\hat{\delta}_{1,IV}$ are inconsistent in the opposite direction to place bounds on the true effect size. The probability limits are

$$\text{plim } \hat{\delta}_{1,OLS} < \delta_1 < \text{plim } \hat{\delta}_{1,IV} \,. \tag{20}$$

That is, an "OLS" regression of (19) gives a lower bound for δ_1 due to measurement error and attenuation bias; and an "IV" regression using contemporaneous interest-rate experiences as the instrument gives an upper bound for δ_1.

Finally, note that since $i^e_{n,t}$ is orthogonal to both structural error terms $u_{n,t}$ and $\xi_{n,t}$, OLS-like estimators of (4) are consistent for the structural coefficient product $\delta_1\alpha_1$. Thus, all our previous estimates linking interest-rate experiences to mortgage choice behavior are consistent under the conditions of this section.

Results. The system of equations (2) and (3) fall under the classic case of using a bivariate probit in a simultaneous equations framework (Heckman (1978), case 3), so, assuming the mortgage choice and interest rate forecast errors (u, ξ) are jointly normal, may be estimated by bivariate probit maximum likelihood (Zellner and Lee 1965; Ashford and Sowden 1970). We estimate the system under this parametric assumption in Table 9.

We begin by estimating the probit regression (19) of mortgage choice on *ex post* interest rate expectations. As just discussed, the presence of an *ex-post* regressor attenuates the coefficient estimate toward 0. In column 1, where we include all mortgages originated after 1983, we expect measurement error to be quite severe, as the timing discrepancy between origination and the survey can be large. In column 2 we restrict the sample to "new" mortgages taken out during the survey year, so the timing discrepancy is minimized to one year.[35]

We observe a positive relationship between expecting higher future interest rates and FRM choice in both samples. As expected, attenuation bias is most severe in the all-mortgages sample. When we restrict to new mortgages only, the coefficient estimate increases by a factor of five (from 0.05 in column 1 to 0.25 in column 2) and is highly significant.

In columns 3 and 4 we jointly estimate the system of equations (2) and (3) by bivariate probit, continuing to restrict to new mortgages. The IV-like estimate in column 3 is significant at a 1% level and (again) five times larger than the OLS-like estimate in column 2. The 95% confidence intervals come close but are non-overlapping: the upper bound in column 2 is 0.42 and the lower bound in column 3 is 0.69. To assess the economic magnitude of the estimated effect, we calculate the additional interest individuals would be willing to pay (WTP) for a fixed-rate mortgage if they were 1 pp more likely to expect higher interest rates (see Section 4.2). Based on the column 2 estimates, the implied additional WTP is $-0.245/-0.232 = 1.06$ pp. (For reference, the standard deviation of the PMMS mortgage spread in 1984–2013 is 0.67 pp.) In column 3, the WTP is $-1.317/-0.246 = 5.35$ pp. These lower and upper bounds on the true effect size indicate a powerful, and potentially expensive, influence of interest-rate expectations on mortgage choice.[36]

Finally, column 4 shows the effect of interest-rate experiences on mortgage choice, the same estimating equation (4) previously analyzed in the RFS. The estimates indicate that households with higher lifetime interest-rate experiences are significantly more likely to choose an FRM than an ARM ($p = 0.026$). This closes the loop with our previous RFS

[35] Each observation in Table 9 is a mortgage, so households with more than one mortgage may appear multiple times in the estimation sample.

[36] As a further robustness check, we re-estimate and confirm the results of Table 9 by LPM. The LPM average marginal effect of expecting higher future interest rates on choosing an FRM is +1.3 pp by OLS on the all-mortgages sample ($p = 0.096$), +5.9 pp by OLS on the new-mortgage sample ($p = 0.013$), and +31 pp by 2SLS on the new-mortgage sample ($p = 0.002$).

analysis, showing that our main analysis replicates in a different dataset, conducted more frequently (triennially rather than decennially), with more household controls (including net worth), and covering a longer time period (1989–2013 rather than 1985–1991 and 1995–2001).

7 Discussion: The Long-Lasting Effects of the Great Inflation

The cost estimates in this paper leave us with a striking conclusion about the long-run consequences of the Great Inflation, both in terms of consumer choices and in terms of welfare implications. Suppose, as shown in Figure 2, that the Great Inflation had not occurred. Using our structural choice model estimates in Table 5, the FRM share would have been 4.1 pp lower across the RFS households. This effect is concentrated among younger households taking out mortgages in the late 1980s—essentially, the Baby Boom generation, many of whom entered the housing market and bought their first homes at this time. Table 10 shows that Boomers would have take out 740,000 fewer FRMs if not for the Great Inflation, lowering their FRM share by 6.1 pp. A decade later, differences between the interest-rate experiences of Boomers and earlier generations recede, but these older generations continue to overweight the 1970s vis-a-vis younger Gen Xes. We estimate that the memory of the Great Inflation raises the FRM share among Baby Boomers' mortgage originations in the late 1990s by 2.7 pp, or 400,000 additional FRMs. In other words, the long shadow of the Great Inflation has significantly altered the composition of one of the largest asset markets in the US, and we can pinpoint the cohorts that are particularly affected.

These decisions are costly. Based on the aggregate of our interest rate estimates, using expected refinancing behavior and mobility, Baby Boomers likely ended up overpaying over \$12.6 billion on their FRMs in the late 1980s, and \$9.1 billion in the late 1990s (under risk-adjusted, Scenario 3 interest-rate predictions), about \$22 billion overall. This represents about 15% of switching Boomers' original mortgage balances, indicating significant overpayment for these households.[37] These calculations underscore the point that young borrowers'

[37] Switching Boomers took out \$147 billion in mortgages over 1985–91 and 1995-2001. All Baby Boomers,

beliefs are particularly affected by macroeconomic shocks, since they have the shortest personal histories of lifetime experiences. Such changes in beliefs can produce long-lasting effects that only temper many years later.

Our results are, however, not restricted to the Great Inflation period. While a large share of the identifying variation in this paper stems from the 1970s, the above cited papers on inflation experiences among US consumers in the Michigan Survey of Consumers (MSC) and among European consumers in the European Household Finance and Consumption Survey (HFCS) document similar magnitudes of experience-based learning. This paper is the first to pinpoint the effects on contract choice, to quantify these effects, and to provide cost estimates. Higher lifetime interest-rate experiences are the determining factor in choosing an FRM for approximately 16 percent of outstanding mortgages, and households exhibit an *ex ante* willingness to pay of 7–17 bp on the FRM mortgage contract for every additional percentage point of lifetime interest-rate experiences. *Ex post* (as of the RFS survey year), the average switching household would have been better off by \$8000 to \$19,000 after accounting for expected refinancing behavior and years of occupancy in the home.

Looking ahead, we can ask whether the experience of the mortgage crisis from 2007–2010 will have similar long-lasting effects and welfare implications for members of the Gen-X and Millennial generations who were first-time homeowners then.

Which policies would ameliorate the costs for consumers? The answer to this question depends on the extent to which these decisions represent a mistake (biased beliefs) versus increased demand for insurance due to non-standard, instable preferences. Our evidence on the influence of experiences on interest-rate beliefs point to a mistake. The cost of this mistake is amplified by other well-known financial household mistakes, such as the failure to refinance optimally, which we accounted for in our analysis. From this perspective,

including both switching and non-switching households, took out a total of \$3.1 trillion; so our WRTE is just over half a percent of this much larger total (\$22B / \$3.1 T = 0.7%).

policy proposals including borrower counseling surrounding the refinancing decision and the marketing of FRMs that refinance automatically (cf. Keys et al. 2016) would help.

Another important dimension are general-equilibrium effects. Increased demand for FRMs by households with biased beliefs about future inflation and interest rates raises the FRM–ARM spread, so the higher mortgage rates paid by behavioral FRM borrowers help finance lower rates paid by non-behavioral ARM borrowers (Gabaix and Laibson 2006). Any policy that encourages greater ARM takeup would raise borrowing costs for these non-behavioral households, unless the reduced need for bank risk management resulted in large cost savings that could be passed through to all borrowers. Nevertheless, to the extent that such cross-subsidization is undesirable, our study suggests that the ARM's low reputation among borrowers is deserving of rehabilitation.

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Table 1: RFS Summary Statistics

	FRM	ARM	Balloon	FRM–ARM
N =	12,416	2,245	735	
Contract Characteristics				
Current rate (bps)	972.7	924.5	870.8	48.2*
Initial rate (bps)	"	876.2	"	96.4*
Margin (bps)	n.a.	282.7	n.a.	n.a.
Years since origination	2.6	2.8	2.1	-0.2*
Original Term (years)	23.2	26.1	8.9	-2.9*
Loan Amount (2000 $k)	102.0	140.3	89.9	-38.3*
Prepayment penalty	0.061	0.091	0.058	0.0*
Economic Conditions (all in %)				
Inflation	3.24	3.35	3.45	-0.12*
FRM–ARM spread	1.75	1.86	1.69	-0.11*
Yield spread	0.90	0.99	0.84	-0.09*
Borrower Characteristics				
Interest rate experiences (%)	6.39	6.37	6.32	0.02*
Inflation experiences (%)	4.74	4.79	4.68	-0.05*
Primary owner age	41.4	41.8	42.8	-0.4
Non-white	0.136	0.099	0.121	0.037*
Hispanic	0.508	0.580	0.516	-0.071*
Veteran	0.226	0.216	0.245	0.010
Joint owners	0.703	0.694	0.660	0.009
First-time owner	0.413	0.348	0.347	0.065*
Has investment income	0.282	0.302	0.256	-0.021
Has business income	0.094	0.106	0.135	-0.012
Total income (2000 $)	75,177	84,165	71,479	-8,989*
Property Characteristics				
Central city of MSA	0.257	0.258	0.214	0.000
Rural county	0.143	0.162	0.310	-0.018*
Second home	0.012	0.017	0.017	-0.005
Mobile home	0.032	0.020	0.049	0.012*
Condo	0.071	0.118	0.057	-0.047*
Other Loan Characteristics				
Junior mortgage	0.129	0.086	0.233	0.043*
Non-conventional	0.211	0.061	0.049	0.150*
Refi	0.256	0.244	0.294	0.012
Loan / income	1.73	2.04	1.54	-0.31*
Loan / value × 100	81.7	90.0	80.2	-8.3*
Loan / CLL	0.426	0.554	0.386	-0.128*
Jumbo loan	0.043	0.127	0.056	-0.084*
Points paid (bps)	39.6	42.1	14.9	-2.5

Notes. The table reports mean values among respondents to the 1991 and 2001 Residential Finance Survey (RFS) of homeowner properties, with origination at most 6 years before the survey year (1985–1991, 1995–2001) and primary-owner age between 25 and 74 years at origination. All statistics are as of the origination year, based on available cases. Investment income and second home status only available for 2001. FRM–ARM spread is from Freddie Mac PMMS, by origination year and Census region. Yield spread is the 10-year minus 1-year yields on constant maturity U.S. Treasuries. All other variable definitions are in Appendix A. * $p < 0.05$.

Table 2: SCF Summary Statistics

All SCF HHs			
	Mean	**SD**	***N***
Respondent age	47.2	13.4	36,266
Married	0.55	0.50	36,266
HH income (2013 $)	87,560	259,644	36,266
HH net worth (2013 $)	477,242	2,888,737	36,266
Homeowner	0.68	0.47	36,266
Mortgage | Howeowner	0.68	0.47	26,219
FRM | Mortgage	0.86	0.35	16,824
Loan/CLL | Mortgage	0.46	0.41	15,708
Jumbo | Mortgage	0.06	0.24	15,446
Non-conventional | Mortgage	0.28	0.45	16,824
Has second mortgage | Mortgage	0.09	0.28	16,824
Has second home	0.19	0.39	36,266
Fraction expecting higher *i*	0.70	0.46	36,266
Fraction expecting lower *i*	0.06	0.25	36,266
Net fraction expecting higher *i*	0.63	0.60	36,266
Interest rate experiences (%)	5.49	0.99	36,266
Inflation experiences (%)	4.09	0.67	36,266

New Mortgages			
	FRM	**ARM**	**FRM – ARM**
N =	*2,538*	*725*	
Respondent age	44.0	44.8	-0.8
Married	0.71	0.73	-0.02
HH income (2013 $)	136,756	205,648	-68,892*
HH net worth (2013 $)	712,055	1,516,472	-804,417*
Loan / CLL	0.47	0.68	-0.21*
Jumbo loan	0.06	0.17	-0.11*
Non-conventional	0.30	0.16	0.14*
Junior mortgage	0.09	0.14	-0.05*
Second home	0.15	0.25	-0.09*
Fraction expecting higher *i*	0.74	0.65	0.08*
Fraction expecting lower *i*	0.06	0.07	-0.02
Net fraction expecting higher *i*	0.68	0.58	0.10*
Interest rate experiences (%)	5.58	5.69	-0.12*
Inflation experiences (%)	4.09	4.18	-0.09*

Notes. The table reports summary statistics for respondents to the 1989–2013 waves of the Survey of Consumer Finances (SCF). The top panel is all respondents aged 25-74; each observation is a household. The bottom panel reports mean values for "new mortgages" that were originated in the survey year only (1989, 1992, ..., 2013); each observation is a mortgage. Calculations use SCF "revised consistent" sampling weights (X42001), rescaled so that each survey wave receives equal weight. We adjust for multiple imputation following Rubin (1987). N reports mean number of observations across implicates. All statistics are based on available cases. * $p < 0.05$.

Table 3: Reduced-Form Logit Model of Mortgage Choice

	(1)	(2)	(3)	(4)	(5)
FRM Alternative-Specific Characteristics					
Freddie Mac PMMS FRM	-0.480**	-0.483**	-3.56***	-3.34***	-3.59***
index rate (%)	(0.235)	(0.235)	(0.55)	(0.57)	(0.81)
Interest rate experiences (%)	0.189**	0.260***	0.256***	0.221***	0.159*
	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)
Log(Income)	-0.0069	-0.0071	-0.0063	0.0277**	0.0278**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.015	-0.012	-0.012	0.024	0.020
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age^2 / 100	0.022	0.022	0.021	-0.017	-0.016
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ARM Alternative-Specific Characteristics					
Freddie Mac PMMS ARM	-0.480**	-0.483**	-0.861***	-0.766***	-0.841***
initial rate index (%)	-	-	(0.242)	(0.249)	(0.311)
Balloon Mortgage Alternative-Specific Characteristics					
Interest rate experiences (%)	-0.278*	0	0	0	
	(0.15)	-	-	-	
Log(Income)	-0.0341*	-0.0345*	-0.0350*	0.0055	
	(0.02)	(0.02)	(0.02)	(0.02)	
Age	-0.027	-0.018	-0.018	-0.030	
	(0.03)	(0.03)	(0.03)	(0.03)	
Age^2 / 100	0.023	0.027	0.028	0.033	
	(0.03)	(0.03)	(0.03)	(0.03)	
Alternative-specific constants	YES	YES	YES	YES	YES
Origination year FE	YES	YES	YES	YES	YES
Mortgage controls				YES	YES
Sociodemographic controls				YES	YES
Number of Choice Situations	15,051	15,051	15,051	15,051	14,337
Number of Alternatives	3	3	3	3	2
Pseudo R^2	0.018	0.017	0.020	0.071	0.069
$-\delta_{ie\text{, FRM}} / \beta_{\text{Rate, FRM}}$	0.394	0.538*	0.072***	0.066***	0.044*
(S.E. by delta method)	(0.255)	(0.300)	(0.023)	(0.025)	(0.025)

Notes. The table reports coefficient estimates for a reduced-form, multinomial logit model of mortgage choice among FRM, Balloon, and ARM alternatives in the 1991 and 2001 RFS. Cols. 1–4 include all three alternatives, while Col. 5 reports binomial logit coefficients, excluding the balloon alternative. The sample is mortgages originated $\leq$ 6 years prior to the survey year, with primary owner age between 25 and 74 years. The omitted category for sociodemographic variables is ARM. Separate coefficients for all mortgage / sociodemographic controls are estimated for each alternative. Mortgage controls are Refi dummy, Junior Mortgage dummy, Non-conventional dummy, Loan / CLL, Jumbo dummy, and Points Paid. Sociodemographic controls are First-time Owner dummy, Joint Owners dummy, and Rural county dummy. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Selection-Corrected Mortgage Rate Equations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is:	FRM Rate		ARM Initial Rate		ARM Margin	
Estimation Method	CLAD	SPSC CLAD	CLAD	SPSC CLAD	OLOGIT	SPSC OLOGIT
Freddie Mac PMMS index rate (%)	84.21***	103.7***	77.32***	86.99***	-11.98***	-7.199**
	(0.79)	(3.40)	(3.31)	(6.29)	(2.54)	(3.00)
Log(Income)	-0.411	-3.122**	1.705	0.448	-1.516	-2.489**
	(0.84)	(1.53)	(2.19)	(2.60)	(1.17)	(1.23)
Joint owners	-4.273*	-26.20***	8.528	-3.032	0.412	-3.771
	(2.47)	(7.46)	(8.24)	(10.13)	(5.16)	(5.29)
Rural county	12.43***	46.37***	55.51***	76.03***	-10.1	-4.018
	(3.55)	(10.34)	(10.68)	(14.15)	(8.25)	(9.14)
Points paid (pctg points)	-1.194*	0.104	-7.843**	-8.616**	0.215	0.809
	(0.70)	(2.20)	(3.33)	(4.29)	(1.75)	(1.78)
First-time owner	7.209***	4.245	16.65**	13.52	1.847	0.294
	(2.41)	(5.92)	(8.06)	(9.65)	(5.07)	(5.00)
Junior mortgage	171.5***	122.2***	194.4***	175.1***	30.51	9.745
	(9.52)	(16.38)	(15.28)	(24.50)	(20.89)	(21.11)
Refi	-25.71***	-43.05***	13.61	-0.358	3.546	-1.326
	(2.94)	(7.47)	(8.69)	(10.71)	(5.79)	(6.25)
Non-conventional	0.201	-182.0***	-45.99**	-35.65	-60.11***	-169.1***
	(2.62)	(31.79)	(19.50)	(51.80)	(10.29)	(39.40)
Loan / CLL	-54.43***	34.72**	-97.59***	-60.25**	-20.13**	-11.35
	(6.27)	(15.82)	(15.23)	(25.41)	(9.70)	(13.27)
Jumbo loan	35.85***	81.07***	60.80***	70.10***	-2.892	-14.03
	(7.81)	(20.77)	(17.75)	(20.45)	(9.60)	(10.31)
Constant[a]	156.2***	202.4***	254.8***	150.0**	-	-
	(11.71)	(27.55)	(33.07)	(71.26)	-	-
Margin reference rate dummies					YES	YES
Observations	12,155	12,155	1,410	1,410	1,490	1,490
Pseudo R2	0.219	0.223	0.270	0.275	0.026	0.031
χ^2 test of H0: no selection bias[b]		46.60		10.29		18.57
[p-value]		[0.000]		[0.505]		[0.137]
Average Selection Bias[c]		-178.5		47.4		-

Notes. The table reports two-step censored least absolute deviation (CLAD) estimates and CLAD semi-parametric selection-corrected (SPSC) estimates of the mortgage rate pricing equations in columns 1–4, and marginal effects of all covariates in an ordered-logit (OLOGIT) estimation, without and with SPSC in columns 5–6. The sample is mortgages originated ≤ 6 years ago as of 1991 and 2001 Residential Finance Surveys, with primary owner age between 25 and 74 years. Dependent variables are FRM, ARM initial, and ARM margin rates expressed in bps. Standard errors (in parentheses) are analytic, robust standard errors in columns 1 and 3, bootstrapped standard errors from 200 repetitions in column 5, and bootstrapped standard errors, adjusted for first-step estimation, from 200 repetitions in columns 2, 4, and 6.

a. SPSC absorbs the intercept into the control function. As suggested by Heckman (1990), we estimate the intercept as the median of $Rate_n - Z_n\hat{\Gamma}_i$ in the subsample of observations n with choice probabilities for alternative i above the 90$^{\text{th}}$ percentile. Columns 5–6 show marginal effects, so no intercept is reported.

b. Test statistic for no selection bias is a quadratic form for the difference in slope parameters: $(\hat{\Gamma}_{SC} - \hat{\Gamma}_{noSC})'\hat{V}^{-1}(\hat{\Gamma}_{SC} - \hat{\Gamma}_{noSC}) \sim \chi^2(L)$, where $L = \text{length}(\Gamma)$ (11, 11, and 13, respectively). We calculate V by bootstrapping the difference 200 times. In column 6, the test statistic is calculated on the underlying ordered logit slope coefficients.

c. Average Selection Bias is average value of the selection poynomial in the subsample choosing the respective FRM or ARM alternative. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Structural Logit Model of Fixed-Rate Mortgage Choice

	(1)	(2)	(3)	(4)	(5)	(6)
Step 2 Selection Correction?	No	Yes	No	Yes	No	Yes
FRM Rate Offered	0.774	-0.911***	-0.310	-0.898***	-0.548	-0.595**
	(0.75)	(0.27)	(0.62)	(0.24)	(0.48)	(0.27)
Initial ARM Rate Offered	-0.378	0.830***	1.050*	0.827***	0.142	0.527*
	(0.62)	(0.25)	(0.61)	(0.23)	(0.39)	(0.29)
ARM Margin Offered			-2.587***	-0.030	3.833***	1.684*
			(0.64)	(0.36)	(1.13)	(0.90)
Interest rate experiences (%)	0.202***	0.158*	0.188**	0.157*	0.150*	0.161*
	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)
Log(Income)	0.00295	-0.00787	-0.0662*	-0.00882	0.0822	0.059
	(0.02)	(0.02)	(0.04)	(0.03)	(0.06)	(0.05)
Joint owners	0.144	-0.036	0.014	-0.035	0.105	0.118
	(0.12)	(0.09)	(0.17)	(0.09)	(0.19)	(0.15)
Rural county	-0.048	-0.522***	-0.982**	-0.524***	0.135	-0.349
	(0.35)	(0.19)	(0.45)	(0.20)	(0.34)	(0.28)
Points paid (pctg points)	-0.015	0.063	0.088	0.063	-0.015	0.018
	(0.04)	(0.04)	(0.08)	(0.04)	(0.07)	(0.06)
Age	-0.011	0.013	-0.004	0.013	0.010	0.018
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age^2 / 100	0.019	-0.010	0.012	-0.009	-0.005	-0.013
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Non-conventional					3.781***	3.138*
					(0.66)	(1.82)
Alternative-specific constants	YES	YES	YES	YES	YES	YES
Origination year FE	YES	YES	YES	YES	YES	YES
Number of Choice Situations	14,337	14,337	14,337	14,337	14,337	14,337
Pseudo R2	0.023	0.065	0.043	0.065	0.064	0.067
$-\delta_{ie,\ \mathrm{FRM}} / \beta_{\mathrm{Rate,\ FRM}}$	-0.261**	0.173*	0.606	0.175*	0.274	0.270*
(S.E. by delta method)	(0.110)	(0.093)	(0.372)	(0.094)	(0.167)	(0.147)

Notes. The table reports binomial logit coefficient estimates for the structural model of mortgage choice between FRM and ARM alternatives in the 1991 and 2001 RFS. The dependent variable equals 1 if an FRM is chosen, and 0 for ARMs. Estimates are produced by a three-step procedure, in which interest rates for both alternatives are predicted (step 2) after correcting for sample selection (step 1) using the estimates from Tables 4 and 3, respectively. The sample is mortgages originated $\leq$ 6 years prior to the survey year, with primary owner age between 25 and 74 years. Bootstrapped standard errors in parentheses, adjusting for first- and second-step estimation, from 200 repetitions. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Additional Interest Paid Due to Interest Rate Experiences

	Scenario 1: Primary Mortgage Market Survey rates				
Time Horizon:	Survey Year	5 years	10 years	15 years	E[tenure | age]
After-tax PDV: (all in $)					
No Refi	2,241	5,220	10,707	16,566	12,547
Expected Refi	-	5,131	7,543	9,818	7,667
Optimal Refi	-	4,496	6,125	7,931	6,365
% switching households	16.2	16.2	16.2	16.2	16.2

	Scenario 2: Risk-adjusted rates, seniority-adjusted ARM margins				
Time Horizon:	Survey Year	5 years	10 years	15 years	E[tenure | age]
After-tax PDV: (all in $)					
No Refi	8,108	13,165	24,432	34,247	25,915
Expected Refi	-	12,558	19,567	24,829	19,119
Optimal Refi	-	11,816	17,961	22,797	17,683
% switching households	16.1	16.1	16.1	16.1	16.1

	Scenario 3: Risk-adjusted rates and ARM margins				
Time Horizon:	Survey Year	5 years	10 years	15 years	E[tenure | age]
After-tax PDV: (all in $)					
No Refi	7,700	12,518	23,212	32,679	24,767
Expected Refi	-	11,916	18,365	23,283	17,983
Optimal Refi	-	11,174	16,760	21,249	16,546
% switching households	16.5	16.5	16.5	16.5	16.5

Notes. The table reports the "welfare-relevant treatment effect" (WRTE) on switching households, measured as the differential after-tax interest + refinancing costs paid by a household choosing an FRM instead of an ARM due to overweighting their interest rate experiences. All dollar figures are in constant year-2000 units. Positive values indicate that the FRM is more expensive than the ARM. To calculate the WRTE on switching households, each household is weighted by their decline in probability of choosing an FRM contract when the experienced inflation coefficient is turned off in the choice model (scenario 1 = Table 3 col. 5, scenario 2 = Table 5 col. 2, scenario 3 = Table 5 col. 6). PDV calculations assume a nominal discount rate of 8% / year (r = .04, π = .04). Predicted interest rates in scenario 1 are from the PMMS, and in scenarios 2 and 3 from Table 4, cols. 2, 4, and 6. In the "No Refi" row, the household holds the initial FRM until maturity. In the "Expected Refi" row, the household is assumed to refinance probabilistically, according to a probit function of the differential between the current FRM rate i_0 and the refinanced rate i, estimated in Andersen et al. (2015) Table 8, column 1. (The timing of principal repayment is the same as in Optimal Refi row.) In the "Optimal Refi" row, the household refinances deterministically whenever $i_0 - i > OT$, where OT is the square-root rule approximation to the optimal threshold for refinancing, derived by Agarwal et al. (2013). The mortgage interest deduction is calculated assuming a 25% marginal tax rate. Refinancing costs $2,000 and is not tax-deductible. "E[tenure | age]" indicates that probability of moving every year estimated as a 4th-order polynomial in head of household's age, using 5-year migration / geographic mobility data from CPS ASEC 2005 and 2010.

Table 7: Monte Carlo Simulation Results

	Mean	SD	10th Pctl.	90th Pctl.	Pct. > 0
WRTE (after-tax $)					
No Refi	13,204	9,467	1,357	24,770	93
Expected Refi	10,383	7,024	202	19,429	90
Optimal Refi	8,856	6,935	-1,144	18,282	88
Economic Conditions (Years 1-30)					
Average inflation (%)	3.70	1.54	1.60	5.67	100
Average one-year interest rate (%)	5.69	1.65	3.77	8.11	100
Average FRM–ARM spread (%)	0.05	0.95	-1.37	1.14	50

Notes. The table reports summary statistics from a Monte Carlo simulation of different possible interest and mortgage rate paths, $T = 30$ years each, using the parameters in Table A.8, based on 100 replications. WRTE is calculated using Scenario 3 household-level interest rates given simulated baseline rates and mobility given borrower age. We use the same experience-induced switching probabilities as in Table 6, from the actual RFS origination years. All other calculation details are the same as in Table 6.

Table 8: Interest-Rate Expectations and Interest-Rate Experiences

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is:	Net Expectation (-1/0/1)		Expect Lower i? (0/1)		Expect Higher i? (0/1)	
Estimation method:	LPM	Ordered Probit	LPM	Probit	LPM	Probit
Interest rate experiences (%)	0.0690***	0.138***	-0.0203***	-0.144***	0.0488***	0.137***
	(0.01)	(0.02)	(0.00)	(0.02)	(0.01)	(0.02)
Survey Year FE?	YES	YES	YES	YES	YES	YES
Number of Households	36,264	36,264	36,264	36,264	36,264	36,264
R^2	0.024		0.008		0.026	
Pseudo R^2		0.016		0.015		0.021
F-stat on i^e	70.04	72.66	30.91	33.4	62.57	63.47

Table 9: Interest-Rate Expectations and Mortgage Choice

	(1)	(2)	(3)	(4)	(5)
Dependent variable is:	FRM	FRM	FRM	Expect higher *i*	FRM
Estimation method:	Probit	Probit	Bivariate Probit		Probit
			(2nd Stage)	(1st Stage)	(RF)
Expect higher *i* (0/1)	0.0535*	0.245***	1.317***		
	(0.03)	(0.09)	(0.32)		
Interest rate experiences (%)				0.215***	0.222**
				(0.08)	(0.10)
FRM–ARM spread (%)	-0.158***	-0.232***	-0.246***		*(Absorbed*
	(0.02)	(0.06)	(0.06)		*by FE)*
Mortgage controls	YES	YES	YES		YES
Sociodemographic controls	YES	YES	YES		YES
Origination year FE				YES	YES
Sample	All Mtgs.	New Mtgs.	New Mtgs.		New Mtgs.
Number of Mortgages	21,330	3,123	3,123		3,123
Pseudo R^2	0.033	0.051	0.098		0.085
ρ			-0.66***		

Notes. Tables 8 and 9 report linear probability model and probit coefficient estimates of (3), relating past interest-rate experiences to expectations, and (2), relating expectations to mortgage choice. "Net expectations" codes households expecting higher rates as +1, lower rates as −1, and about the same as 0. "FRM" is an indicator equal to 1 if the household chose an FRM, and 0 if it chose an ARM. All other variable definitions are in Appendix A. Mortgage controls are Refi dummy, Junior Mortgage dummy, Non-conventional dummy, Loan / CLL, and Jumbo dummy. Sociodemographic controls are log(Income), log(Net Worth), Age, Age^2, and Married dummy. The Table 8 sample consists of all SCF households with a respondent aged 25–74 in survey waves 1989–2013. In Table 9, the "All Mtgs." sample contains all mortgages originated in 1984 or later (when PMMS ARM data begin) of SCF respondents aged 25–74 in survey waves 1989–2013; the "New Mtgs." sample further restricts to mortgages originated in the survey year (1989, 1992, ..., 2013). Because some households have multiple mortgages, number of mortgages exceeds number of mortgagors in Table 2. Regressions use SCF "revised consistent" sampling weights (X42001), rescaled so that each survey wave receives equal weight. We adjust for multiple imputation using the Rubin (1987) methodology. Number of observations is based on first implicate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Aggregate Cost of the Great Inflation

(1)	(2)	(3)	(4)	(5)
Survey Year – Cohort	% Switching HHs	E[WRTE] per switching HH ($)	# of switching HHs (1000s)	Total Cost ($m)
1991 – G.I. & Silent Gens.	5.2	20,291	318.9	6,471
1991 – Baby Boomers	6.1	17,032	742.2	12,641
1991 – Gen Xers	4.4	10,647	8.6	92
2001 – G.I. & Silent Gens.	2.5	20,439	128.2	2,621
2001 – Baby Boomers	2.7	22,296	406.9	9,072
2001 – Gen Xers	2.0	15,834	121.9	1,931

Notes. The table reports the aggregate additional interest paid (in 2000 $) by members of each generation who chose an FRM instead of an ARM because of their interest rate experiences during 1968-84, among mortgages originated ≤ 6 years prior to survey year. The G.I. and Silent Generations are individuals born prior to 1946; Baby Boomers are born between 1946 and 1964; and Gen Xers are born after 1964. Column (2) shows the predicted change in the FRM product share if the Great Inflation had not occurred, as shown in Figure 2. Column (3) shows the Scenario 3 WRTE under expected refinancing and mobility given age. Column (4) assumes that every sample household represents 2,599 population HHs in 1991 and 3,655 population HHs in 2001. Column (5) = Column (3) $\times$ Column (4).

Online Appendix

A Variable Definitions

RFS Variables (Census Bureau)

Variable	Units	Description
FRM Rate, ARM Initial Rate, ARM Margin	% or bps	Contractual interest rates charged to mortgage borrowers, top-and bottom-censored. 1991 RFS rates are also interval-censored; we code these to interval midpoints.
Total Income	const. year 2000 $	Real total household income in origination year. We impute total household income in Census year (1990 or 2000) back to origination year using peak-to-peak log growth rate in U.S. nominal median household income over 1980-2001 from CPS Historical Table H-6 (4.14% / year), then inflate to constant year 2000 dollars. For 1991 RFS, income is imputed back to interval midpoints (1985.5 for 1985-86, 1987.5 for 1987-88, and 1990 for 1989-91). Real income is bottom-coded to $1 in log specifications.
Age	years	Primary owner's age in origination year = age in survey year − (survey year − origination year). For 1991 RFS, age is coded to average within each origination year interval.
Joint owners	$\{0,1\}$	=1 if number of property owners exceeds one.
Rural county	$\{0,1\}$	=1 if property is located outside of an MSA.
Junior mortgage	$\{0,1\}$	=1 for second or third mortgage on a property.
Non-conventional	$\{0,1\}$	=1 if mortgage is FHA-, VA-, or FmHA/RHS-insured or guaranteed.
LTI ratio	fraction	Face amount of loan at origination / total household income in origination year. Ratio is symmetrically 1% Winsorized in pooled RFS sample of all FRM / ARM / balloon mortgages.
LTV ratio	fraction	Face amount of loan at origination / property value at origination (2001 RFS) or purchase price (1991 RFS). Ratio is symmetrically 1% Winsorized in pooled RFS sample of all FRM / ARM / balloon mortgages.
Loan / CLL	fraction	Face amount of loan at origination / Conforming Loan Limit for properties with same number of units. The CLL is updated every October. For 1991 RFS, we use the maximum CLL within each origination year interval (generally the last year). Ratio is symmetrically 1% Winsorized in pooled RFS sample of all FRM / ARM / balloon mortgages.
Jumbo loan	$\{0,1\}$	=1 if Loan / CLL > 1.
Points paid	% or bps	Discount points paid as interest at inception of first mortgage, excluding loan origination and non-interest fees.

SCF Variables (Federal Reserve Board)

Variable	Units	Description	SCF Source
Expect Higher i	$\{0,1\}$	=1 if expects higher interest rates five years from now	X302=1
Expect Lower i	$\{0,1\}$	=1 if expects lower interest rates five years from now	X302=2
Net expectation	$\{-1,0,1\}$	= Expect Higher i − Expect Lower i	X302
Married	$\{0,1\}$	=1 if married	X8023=1
Age	years	Age of survey respondent	X8022

Variable	Units	Description	SCF Source
Total Income	const. year 2013 $	1989,1992: total HH income in survey year − 1. 1995–2013: "normal" income (i.e., permanent income) in survey year − 1. Bottom-coded to $1 in log specifications.	1989,1992: Summary Extract Data. 1995-2013: =X7362 if X7650 in (1,2), =X5729 o/w.
Net Worth	const. year 2013 $	HH net worth in survey year. Bottom-coded to $1 in log specifications.	Summary Extract Data
Home owner status	$\{0, 1\}$	0 if rents, 1 if owns (including ranch, farm, mobile home, house, condo), missing otherwise	same as Summary Extract SAS code (FRB website)
Has mortgage	$\{0, 1\}$	=1 if has a mortgage on primary or secondary residence (excluding land contracts).	Any of X723=1, X830=1, X1711=1, X1811=1
Refi status	$\{0, 1\}$	(First mortgage on primary residence only) 1989,1992: =1 if origin. year > purchase year. 1995-2013: =1 if reports taking out this loan to refinance a previous loan.	1989,1992: origin year is X802; purchase year is X606, X626, X630, X634, or X720. 1995-2013: X7137 in (1, 3).
Junior mortgage	$\{0, 1\}$	=1 if second mortgage (primary residence only)	X830=1
Non-conventional	$\{0, 1\}$	=1 if the first or main mortgage is federally guaranteed (includes FHA, VA, and "other programs").	X724=1
Loan amount	$	Original loan amount	X804, X904, X1714, X1814

Other Variables

Variable	Units	Description	Source
Lifetime experiences of interest rates, inflation, etc. (x^e)	%	Weighted average of x over all non-missing values in respondent or primary owner's lifetime, using linearly decreasing weights from origination year to birth year (equation (5)). For the 1991 RFS, we calculate experiences as of the first year in each origination year interval (1985, 1987, and 1989).	Authors' calculations
Interest rate	%	Annual average market yield on 90-day T-bills (1934–present) and 3–6 month Treasury notes or certificates (1920–33).	1920–41: Federal Reserve (1943) *Banking and Monetary Statistics*, Table 122. 1941–63: Federal Reserve (1966) *Supplement to Banking and Monetary Statistics*, Section 12, Table 7. 1962–present: Federal Reserve *Bulletins*, reproduced in FR H.15 release. Cf. FRED series TB3MS and *Historical Statistics of the United States, Millennial Edition* (Carter et al. 2006) series Cj1232.
Inflation	%	Log change in annual average CPI-U.	BLS; Robert Shiller's website
Long-term interest rate	%	Combined long-term U.S. government bond yield	Pre-1960: HSUS (2006) series Cj1192. 1960–present: OECD *Main Economic Indicators*

Variable	Units	Description	Source
(*Ex post*) Real interest rate	%	Interest rate − Inflation	Authors' calculations from *op. cit.*
Yield curve slope	%	Long-term interest rate − Interest rate	Authors' calculations from *op. cit.*
PMMS Index Rates	% or bps	Average rate on an FRM, or average first-year "teaser" rate on a 1/1 ARM, offered to a first-lien, prime, conventional, conforming mortgage borrower with an LTV of 80% and a 30-year term. Annual average of weekly data, re-weighted from five Freddie Mac regions to four Census regions using 1990 Census housing unit counts by state. We use the corresponding Freddie Mac regional rate if borrower's home state is reported, and the Census region rate otherwise.	Freddie Mac Primary Mortgage Market Survey (PMMS)
CLL	$	Conforming Loan Limit	Fannie Mae

B International Mortgage and Inflation Data

Country	Mortgage Type	Source (Mortgage Data)	Median Inflation	Source (Inflation Data)
Algeria	Fixed	Ehlers and Villar (2015)	4.09	IMF (2020)
Argentina	Mixed	Ehlers and Villar (2015)	8.48	World Bank (2020)
Australia	Variable	Lea (2010)	2.47	OECD (2020)
Austria	Variable	Albertazzi et al. (2019)	2.00	OECD (2020)
Belgium	Fixed	Albertazzi et al. (2019)	2.01	OECD (2020)
Brazil	Fixed	Ehlers and Villar (2015)	6.27	OECD (2020)
Canada	Variable	Lea (2010)	1.98	OECD (2020)
Chile	Fixed	Ehlers and Villar (2015)	3.03	OECD (2020)
China	Variable	Warnock and Warnock (2007)	2.00	OECD (2020)
Colombia	Fixed	Ehlers and Villar (2015)	4.65	OECD (2020)
Croatia	Variable	Reuters (2017)	2.14	World Bank (2020)
Cyprus	Mixed	Ehrmann and Ziegelmeyer (2014)	2.30	World Bank (2020)
Czech Republic	Mixed	Ehlers and Villar (2015)	2.03	OECD (2020)
Denmark	Mixed	Lea (2010)	1.76	OECD (2020)
Estonia	Mixed	Swedish Bankers' Association (2018)	3.43	OECD (2020)
Finland	Variable	Scanlon and Whitehead (2004)	1.13	OECD (2020)
France	Mixed	Lea (2010)	1.65	OECD (2020)
Germany	Variable	Lea (2010)	1.51	OECD (2020)
Greece	Mixed	Albertazzi et al. (2019)	2.90	OECD (2020)
Hungary	Mixed	Kubas (2018)	4.07	OECD (2020)
Iceland	Variable	Bjarnason (2014)	3.99	OECD (2020)
India	Mixed	Campbell et al. (2012)	5.83	OECD (2020)
Indonesia	Variable	Ehlers and Villar (2015)	6.21	OECD (2020)
Ireland	Variable	Lea (2010)	1.95	OECD (2020)
Israel	Variable	Ehlers and Villar (2015)	1.10	OECD (2020)

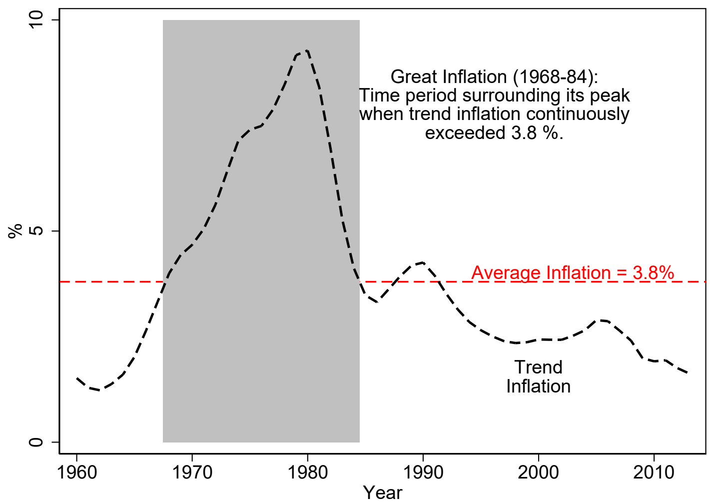
Country	Mortgage Type	Source (Mortgage Data)	Median Inflation	Source (Inflation Data)
Italy	Mixed	Albertazzi et al. (2019)	1.91	OECD (2020)
Japan	Variable	Lea (2010)	-0.03	OECD (2020)
Kenya	Variable	The World Bank (2011)	9.23	World Bank (2020)
Latvia	Variable	Albertazzi et al. (2019)	2.73	OECD (2020)
Lithuania	Variable	Scanlon and Whitehead (2004)	1.85	OECD (2020)
Luxembourg	Mixed	Albertazzi et al. (2019)	2.15	OECD (2020)
Malaysia	Variable	Endut and Hua (2009)	1.92	World Bank (2020)
Malta	Variable	Central Bank of Malta (2018)	1.86	World Bank (2020)
Mexico	Fixed	Ehlers and Villar (2015)	4.13	OECD (2020)
Morocco	Mixed	Dübel et al. (2016)	1.39	World Bank (2020)
Netherlands	Variable	Lea (2010)	1.70	OECD (2020)
New Zealand	Variable	Fitch Ratings (2020)	2.20	OECD (2020)
Norway	Variable	Almklov and Tørum (2007)	2.17	OECD (2020)
Poland	Variable	Ehlers and Villar (2015)	2.22	OECD (2020)
Portugal	Mixed	Swedish Bankers' Association (2018)	2.32	OECD (2020)
Romania	Variable	Hegedüs and Struyk (2005)	5.69	World Bank (2020)
Russia	Fixed	Hegedüs and Struyk (2005)	9.34	OECD (2020)
Singapore	Variable	Ehlers and Villar (2015)	0.98	World Bank (2020)
Slovakia	Variable	Kubas (2018)	2.73	OECD (2020)
Slovenia	Variable	Albertazzi et al. (2019)	2.13	OECD (2020)
South Africa	Variable	Everything Overseas (2016)	5.51	OECD (2020)
South Korea	Mixed	Ehlers and Villar (2015)	2.40	OECD (2020)
Spain	Variable	Albertazzi et al. (2019)	2.62	OECD (2020)
Sweden	Mixed	Scanlon and Whitehead (2004)	1.26	OECD (2020)
Switzerland	Variable	Lea (2010)	0.64	OECD (2020)
Thailand	Variable	Ehlers and Villar (2015)	1.85	World Bank (2020)
Turkey	Fixed	Ehlers and Villar (2015)	8.87	OECD (2020)
Ukraine	Fixed	Cerutti et al. (2015)	11.46	World Bank (2020)
United Kingdom	Variable	Lea (2010)	2.05	OECD (2020)
United States	Fixed	Lea (2010)	2.20	OECD (2020)

Notes. Mortgage Type is one of three classifications: *Variable* indicates that at least 75% of all mortgages in that country have variable interest rates throughout or after an initial period of at most five years; *Mixed* indicates that at least 25% but less than 75% of all mortgages have variable interest rates; and *Fixed* indicates that less than 25% of all mortgages have variable interest rates after at most five years. Median Inflation is the median inflation in a given country from 2000 to present.

C Dating the Great Inflation

We determine the dates for the Great Inflation in a data-driven manner, proposed by Scrimgeour (2008). We first extract the trend component of BLS CPI-U log annual inflation using

Figure A.1



a triangular moving-average filter:

$$\pi_t^{trend} = \sum_{j=-h}^{h} \frac{h - |j|}{h^2} \pi_{t+h}, \tag{A.1}$$

with half-width $h = 4$ years. We then identify those years surrounding the mid-1970s when trend inflation *continuously* exceeded a pre-determined threshold, its 1960–2013 mean of 3.8%. This methodology determines that the US Great Inflation began in 1968 and lasted through 1984. Scrimgeour (2008) calculates dates of 1969–1983 using the GDP deflator and a 4% threshold. Other authors suggest a starting dates as early as 1965; see the references cited in Scrimgeour.

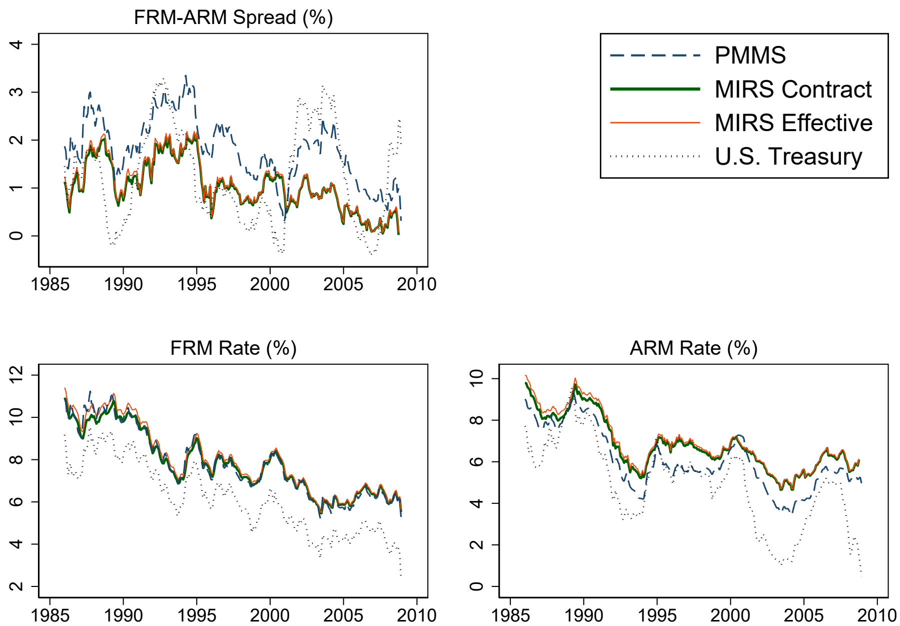
D Comparison of Mortgage Rates in PMMS and MIRS

This overview of the PMMS and MIRS draws on summaries in Koijen et al. (2009) Appendix A, a 2019 Federal Register filing by the FHFA (84 Fed. Reg. 32,738), and Freddie Mac's website.[38]

Freddie Mac's PMMS is based on a representative nationwide survey of lenders (including thrifts, credit unions, commercial banks, and mortgage companies) collected Monday through Wednesday and released every Thursday. Lenders provide quotes for first-lien, conventional,

[38] See http://www.freddiemac.com/pmms/about-pmms.html.

Figure A.2. FRM and ARM Rates in PMMS and MIRS



Notes. The figure shows monthly data from the FHFA's Monthly Interest Rate Survey (MIRS) and Freddie Mac's Primary Mortgage Market Survey (PMMS) (monthly average of weekly data), January 1986–October 2008. US Treasury rates are 10-year minus 1-year spread (top left), 10-year rate (bottom left) and 1-year rate (bottom right).

non-jumbo, home purchase mortgages with an 80% LTV and a 30-year term that a prime borrower would receive that week, so the quotations hold borrower and loan characteristics constant both across products and over time. As of 2009 the PMMS included around 125 lenders per week; as of 2019 the sample size was around 80 lenders per week. Interest rates are a weighted average based on lender size. The PMMS has added and subtracted products over time as the mortgage market has evolved, including the 30-year FRM since its inception (April 1971) and adding a 15-year FRM (August 1991–present); a 1/1 ARM (January 1984–December 2015); and a 5/1 "hybrid" ARM (January 2005–present). Data for five regions of the US were also broken out through December 2015.

The MIRS was launched by the Federal Home Loan Bank Board (FHLBB) in the 1960s, then taken over by the Federal Housing Finance Board (FHFB) in 1989 and by the Federal Housing Finance Agency (FHFA) in 2008. Lenders provide information "on the terms and conditions on all conventional, single-family, fully amortized, purchase-money mortgage loans closed during the last five working days of the preceding month" (Federal Register 2019). Similar to PMMS, the MIRS excludes refinancings, FHA- or VA- insured or guaranteed loans, and multifamily properties; unlike PMMS, MIRS includes non-conforming (jumbo) loans. Koijen et al. (2009) report that the June 2006 MIRS had data from 74 lenders. By 2018 the sample size had shrunk to 20 lenders. In May 2019 a single respondent accounting for more than half of the loans informed FHFA that it was dropping out, leading to the survey's discontinuation. Breakouts of interest rates and other loan terms by property type, by lender type, and by region are available at various frequencies. Separate interest rate data for FRMs and ARMs are available between January 1986 and October 2008, after which the FHFA stopped reporting ARM data due to insufficient observations. Averages were weighted by lender size and type through 2011, and unweighted starting in 2012.

This summary highlights at least three important differences. First, MIRS tends to track PMMS with a lag, since MIRS reflects originations of mortgages that had their rates quoted and locked in several months earlier. The FHFA's 2019 analysis found that an 11-week lag provides the best fit when constructing a transition index from MIRS to PMMS. Second, MIRS is a survey of originations and so reflects changing borrower and loan characteristics across products and over time (including term, LTV, and credit score) whereas PMMS attempts to hold these characteristics fixed. Third, MIRS includes "hybrid" ARMs with initial fixation periods longer than a year in its ARM summary data—e.g., rates on the 1/1 ARM and the 5/1 ARM are averaged together—while PMMS breaks these rates out separately. Hybrid ARMs will tend to carry higher initial rates than 1/1 ARMs since they provide insurance against rising interest rates for a longer initial time period.[39]

Table A.5 reports that the average "contract" FRM rate in MIRS is very close to the

[39] Between 2005 and 2015, when the PMMS reports both, the 5/1 ARM initial rate is 38 basis points higher on average.

Table A.5: PMMS and MIRS Summary Statistics

Variable	Source	Mean	SD	10th Pctl.	90th Pctl.
FRM Rate	PMMS	7.85	1.58	5.92	10.27
FRM Rate, Contract	MIRS	7.84	1.47	6.03	10.05
FRM Rate, Effective	MIRS	8.03	1.58	6.09	10.43
ARM Rate	PMMS	6.04	1.46	4.18	8.39
ARM Rate, Contract	MIRS	6.79	1.26	5.33	8.84
ARM Rate, Effective	MIRS	6.94	1.34	5.40	9.07
FRM–ARM Spread	PMMS	1.81	0.66	0.88	2.71
FRM–ARM Spread, Contract	MIRS	1.05	0.52	0.37	1.84
FRM–ARM Spread, Effective	MIRS	1.09	0.53	0.40	1.89

Notes. The table reports summary statistics for the FRM and ARM initial rates and spreads reported in PMMS and MIRS, monthly averages over January 1986–October 2008. All variable are in percentage points.

PMMS, and that the average "effective" rate in MIRS that includes origination points and fees is only a little higher, about 18 basis points. By contrast, the average ARM rates in MIRS are 75 to 90 basis points higher than the average ARM rate in PMMS. Figure A.2 plots the rates and spreads over time; it is visually apparent that FRM–ARM spreads are consistently lower in MIRS, and that this difference is largely due to consistently higher initial ARM rates in MIRS. One possible explanation is the rise in popularity of hybrid ARMs in the early aughts, with initial fixation periods as long as 10 years (cf. Koijen et al. 2009, Figure 5); these carry higher rates and are included in MIRS but not PMMS. Were this the cause, we would expect the MIRS–PMMS difference to increase in the early aughts. Inspection of the data underlying Figure A.2 reveals a local maximum difference in ARM rates in 2004–5, consistent with this hypothesis, but also in 1992–4 and 1996–7, well before the explosion in popularity of hybrid ARMs. Moreover, Figure 5 in Koijen et al. (2009) also indicates a spike in hybrid ARM popularity in 2000, but in this year the MIRS ARM contract rate actually fell *below* the PMMS rate (bottom-right panel of Figure A.2). This suggests that hybrid ARMs are not the entire story. Despite these level differences, the series track each other quite closely. The correlation coefficients among the three spread series exceed 80% (Table A.6).

Table A.6: Correlations Among FRM-ARM Spreads in PMMS and MIRS and 10 Year−1 Year Treasury Yield Spread

	Treasury	PMMS	MIRS Contract	MIRS Eff.
10Y−1Y Treasury Yield Spread	1.000			
PMMS FRM-ARM	0.643	1.000		
MIRS FRM-ARM, Contract	0.411	0.819	1.000	
MIRS FRM-ARM, Effective	0.397	0.812	0.998	1.000

Notes. The table reports Pearson correlation coefficients among the U.S. Treasury 10-year minus 1-year yield spread and the FRM-ARM spreads from PMMS and MIRS, monthly averages over January 1986–October 2008.

Table A.6 also reveals that the PMMS tracks the US Treasury yield curve much more closely than MIRS. The correlation between the 10-year minus 1-year Treasury yield spread and the PMMS FRM–ARM spread is 0.643,indicating that the yield spread explain $0.643^2 \approx 41\%$ of the variation in PMMS. By comparison, the yield spread only explains $0.411^2 \approx 17\%$ and $0.397^2 \approx 16\%$ of the MIRS spreads. This suggests that non-interest factors drive the remaining variation in MIRS to a greater extent than PMMS, possibly due to changes in the borrower and loan pool changes over time.

E Methodology in Detail

E.1 Estimation Methodology with $J \geq 2$ Alternatives

Our key prediction is that relatively high lifetime experiences of interest rates are a significant factor in explaining the tilt in mortgage financing toward fixed-rate contracts. As the main estimation approach we utilize a multinomial, discrete-choice model over mortgage products using a three-step procedure suggested by Lee (1978) and Brueckner and Follain (1988):

1. Estimate a reduced-form model of mortgage choice using only *exogenous* explanatory variables (equation (8)).

2. Predict FRM and ARM mortgage rates at the household level, correcting for selection bias (equation (7)).

3. Estimate a structural model of mortgage choice using individual-level predicted mortgage rates (equation (6)).

We begin by assuming that a household n derives utility $U_{n,j} = x'_{n,j}\beta_j + \upsilon_{n,j}$ when choosing alternative j from a menu of $J \geq 2$ alternatives (e.g., $j \in \{FRM,\ ARM,\ Balloon\}$), depending on observed components $x'_{n,j}\beta_j$ and unobserved components $\upsilon_{n,j}$ (equation (1) in the paper). Each household lives in Census region r and chooses a mortgage only once, in year t (unless they take a junior mortgage), so we omit time subscripts for notational simplicity. Observed components may include attributes of the alternative, such as its cost, as well as household characteristics that sway the decision toward one alternative. The latter includes our variable of interest, namely past lifetime experiences such as living through the Great Inflation. Alternative j is chosen by household n if

$$\begin{aligned} D_{n,j} &:= \mathbb{I}\{U_{n,j} > U_{n,k} \quad \forall k \neq j\} \\ &= \mathbb{I}\{\upsilon_{n,k} - \upsilon_{n,j} < x'_{n,j}\beta_j - x'_{n,k}\beta_k \quad \forall k \neq j\} \end{aligned} \tag{A.2}$$

equals 1.[40] Marley (cited by Luce and Suppes (1965)) and McFadden (1974) show necessary and sufficient conditions on the distribution of the unobserved utility components υ_{nj} for the implied choice probabilities $\Pr(D_{n,j} = 1) = F(x'_{n,j}\beta_j - x'_{n,1}\beta_1, \ldots, x'_{n,j}\beta_j - x'_{n,J}\beta_J)$ to be described by a logit formula. This likelihood function is globally concave in β, so that the utility parameters can be estimated by maximum likelihood (up to scale).[41] The definition of $D_{n,j}$ implies that, if explanatory variables do not vary across alternatives within household ($x_{n,j} = x_n \quad \forall j$), as is the case for borrower characteristics, then β_j can only be estimated for $J - 1$ of the J alternatives. We normalize $\beta_{\cdot,ARM} \equiv 0$ for all borrower characteristics, including experienced interest rates. (This is equivalent to taking utility differences versus the base-case ARM, as in equation (2) in the paper.)

Plugging (3) into (1) and expanding borrower and mortgage characteristics x gives:

$$U_{n,j} = \beta_{0,t,j} + \beta_{R,j} Rate_{n,t,j} + \beta_{ie,j} i^e_{n,t} + \beta_{Inc,j} Income_n + f_j(Age_n) + \upsilon_{n,j}\,. \tag{A.3}$$

[40] Since utility is continuous, ties are of probability zero and are broken at random.

[41] That is, the ratios of utility slope coefficients are identified, but the levels are not. We follow the usual practice of normalizing the variance of the υ's to $\pi^2/6$ before estimating the coefficients.

Our main observable characteristics are the alternative-specific interest rate offered to the borrower, $Rate_{n,t,j}$; the borrower's (log) income, $Income_n$; and an alternative-specific function of the borrower's age, $f_i(Age_n)$. Our baseline age specification is quadratic, to capture possibly non-linear life-cycle variation in the attractiveness of a given mortgage contract type. The explanatory variable of interest is borrower n's lifetime experience of interest rates at the time of the choice situation, $i^e_{n,t}$. Since each borrower is only observed once, we omit the time subscripts on all borrower characteristics, even though some characteristics such as income are time-varying.

In the presence of year fixed effects, a borrower's lifetime interest-rate experiences should not matter unless there is a correspondence between those experiences and borrower beliefs that differs from the baseline rational-expectations forecast. Specifically, the experience-effect hypothesis implies $\beta_{ie,FRM} > 0$, while the standard rational framework predicts $\beta_{ie,FRM} = 0$.

The main estimation difficulty is that the interest rates of the non-chosen alternatives are not observed. If households were randomly assigned to mortgage types, we could simply estimate the correlation between borrower characteristics and interest rates using the subsample of borrowers who chose each alternative. Specifically, we would use the subset of households n choosing alternative i to estimate the following equation (equation (7) in the main paper) for all J alternatives:

$$\begin{aligned} Rate_{n,j} &= \gamma_{0,j} + Z'_{n,j}\Gamma_{n,j} + \zeta_{n,j} \\ &= \gamma_{0,j} + \gamma_{R,j} PMMSRate_{r,t,j} + z'_n\gamma_j + \zeta_{n,j}\,. \end{aligned} \tag{A.4}$$

The equation decomposes the explanatory variables $Z_{n,j}$ into $(PMMSRate_{r,t,j}, z'_n)'$, where the Freddie Mac survey rate $PMMSRate_{r,t,j}$ represents the baseline price charged to a high-quality borrower in the same year y and Census region r as borrower n, taking out mortgage product j; and the other explanatory variables z_n control for household-varying risk proxies such as income, first-time homeowner status, marital status, urban/rural property location, and loan size. The specification includes the same controls in each rate equation but allow them to have different slope coefficients γ_j. The error term $\zeta_{n,j}$ captures all remaining, unobserved factors that affect the interest rate for alternative j being offered to household n.

The goal of estimating equation (A.4) is to predict interest rates for households who did not choose product j. However, since households were not randomly assigned to mortgage types, OLS will likely be inconsistent due to selection bias. Specifically, households might have been offered an unusually low rate for the alternative they chose, so we expect the mean pricing error to be negative rather than zero: $\mathbb{E}\left[\zeta_{n,j} \mid Z_{n,j}, D_{n,j}=1\right] = f(Z_{n,j}) < 0$. Our estimation must account for a correlation between the explanatory variables $Z_{n,j}$ and factors affecting sample selection. Otherwise our out-of-sample predictions will also be biased and inconsistent.

An additional wrinkle is that mortgage rates are top-coded in the public-use RFS files (at 14.1% in the 1991 survey and at 20% in 2001), and censoring of the dependent variable leads to inconsistent OLS estimators. Moreover, parametric methods such as Tobit do not perform well in the presence of non-normal errors. Powell (1984) first observed that estimators based on a conditional *median* restriction $\mathbb{E}\left[\operatorname{sgn}(\zeta_{n,j}) \mid Z_{n,j}\right] = 0$, rather than the usual conditional mean restriction $\mathbb{E}\left[\zeta_{n,j} \mid Z_{n,j}\right] = 0$, are robust to top- and bottom-censoring of the dependent variable, without further assumptions on the distribution of the errors. We thus use a censored least absolute deviations (CLAD) estimator as our benchmark estimator of equation (A.4).

Although our coefficient estimates from (A.4) do not provide us directly with predicted rates, we can plug them into (A.3) and obtain a *reduced-form* choice model that we can estimate (equation (8) in the main paper):

$$
\begin{aligned}
U_{n,j} &= \tilde{x}_{n,j}'\tilde{\beta} + \tilde{\upsilon}_{n,j} \\
&= \tilde{\beta}_{0,j,t} + \tilde{\beta}_{R,j} PMMSRate_{r,t,j} + \beta_{ie,j} i^e_{n,t} + \tilde{\beta}_{Inc,j} Income_n + f_j(Age_n) + \tilde{z}_n'\tilde{\gamma}_j + \tilde{\upsilon}_{n,j} \, .
\end{aligned}
\tag{A.5}
$$

We place tildes on coefficients and variables that represent different objects than in equation (A.3). For example, the coefficient on the PMMS rate in equation (A.5) is the structural coefficient from equation (A.3), scaled by the partial correlation between household interest rates and PMMS rates from equation (A.4): $\tilde{\beta}_{R,j} := \beta_{R,j}\gamma_{R,j}$. We write $\tilde{z}_n$ to represent the subset of variables in z_n from equation (A.4) that do not appear directly in (A.3) (e.g., excluding household income). The pricing errors from (A.4), ζ_{nj}, are absorbed into the unobserved component of latent utility: $\tilde{\upsilon}_{n,j} := \upsilon_{n,j} + \beta_{R,j}\zeta_{n,j}$.

The important takeaway is that we have eliminated the missing data problem by replacing household-level interest rates $Rate_{n,t,j}$ with the regional Freddie Mac survey rates $PMMSRate_{r,t,j}$, which do not depend on an individual household's characteristics and are always observed for both alternatives. Moreover, since lifetime interest-rate experiences do not appear in equation (A.4), we can consistently estimate the structural coefficient $\beta_{ie,j}$ in the reduced-form choice model.

We now have all the pieces in hand to run our three-step estimator and obtain structural mortgage choice estimates. We work backward, estimating (A.5) first, (A.4) second, and (A.3) third. Model (A.5) can be consistently estimated by standard maximum likelihood methods, since it only depends on exogenous characteristics that are observed for all households. We then use the predicted choice probabilities to correct for any selection bias in the FRM and ARM rate equations (A.4) semiparametrically. Specifically, let $\tilde{\eta}_{n,j,k} := \tilde{x}_{n,j}'\tilde{\beta}_j - \tilde{x}_{n,k}'\tilde{\beta}_k$ denote the difference in the observed components of utility for the

j^{th} and k^{th} alternatives. We can decompose the rate equation error in equation (A.4) as

$$\zeta_{n,j} = \mathbb{E}\left[\zeta_{n,j} \mid Z_{n,j}, D_{n,j} = 1\right] + w_{n,j} = \mathbb{E}\left[\zeta_{n,j} \mid Z_{n,j}, \tilde{\upsilon}_{n,k} - \tilde{\upsilon}_{n,j} < \tilde{\eta}_{n,j,k}\ \forall j \neq i\ \right] + w_{n,j}$$
$$= g(\tilde{\eta}_{n,j,1}, \ldots, \tilde{\eta}_{n,j,J}) + w_{n,j}\,, \tag{A.6}$$

where $w_{n,j}$ is a mean-zero error that is independent of $(Z'_{n,j}, D_{n,j})'$. This decomposition states that, conditional on selection, the mean of the pricing error depends on $Z_{n,j}$ only through the $J-1$ choice indices $\tilde{\eta}_{n,j,1}, \ldots, \tilde{\eta}_{n,j,J}$.

Newey (2009) analyzes the case $J = 2$ and suggests a semiparametric selection correction (SPSC) estimator that uses a series approximation for the selection bias term: $g(\tilde{\eta}_{n,j,k}) \approx \sum_{l=0}^{L} \tau_l \cdot p(\tilde{\eta}_{n,j,k})^l$, where $p(\cdot)$ is some function, and τ_l is the coefficient on the l^{th} polynomial term. Consistency of the two-step series estimator requires that the order L of the approximating power series grows with sample size N according to $L = o(N^{1/7})$. Plugging the approximation terms into equation (A.4), we obtain

$$Rate_{n,j} \approx \gamma_{R,j} PMMSRate_{r,t,j} + z'_n\gamma_j + \sum_{l=0}^{L} \tau_l \cdot p(\tilde{\eta}_{n,j,k})^l + w_{n,j}\,. \tag{A.7}$$

In the special case where $L = 1$ and $p(\cdot)$ is the inverse of Mill's ratio, equation (A.7) is the familiar Heckman (1979) two-step selection model. Newey (2009) establishes the consistency and root-N asymptotic normality of this semiparametric, two-step series estimator $\hat{\Gamma}_{n,j}$ when $L \to \infty$, without requiring joint normality of the pricing and selection equation errors.

We use $p(\cdot) = 2F(\cdot) - 1$ with F the logit CDF, choosing the order L of the approximating power series to the selection-bias term by leave-one-out cross-validation. For a sample size of 14,337 mortgages, the results above suggest an upper bound of $14337^{1/7} \approx 4$. We run the two-step estimation of equation (A.7) for $1 \leq L \leq 4$, on all possible leave-one-out subsamples, for both the FRM and ARM rate equations. The mean absolute prediction error is minimized at $L = 4$ for both rates.

Note that specification (A.7) drops the intercept $\gamma_{0,j}$ from (A.4) since the series approximation includes a possibly non-zero constant (for $l = 0$). Thus, unlike in Heckman's two-step model, the model intercept $\gamma_{0,j}$ is not separately identified from the selection control function $g(\cdot)$.

Identification of the slope parameters requires a "single-index restriction" on the first-step selection process: $\Pr(D_{n,j} = 1 \mid \tilde{x}'_{n,j}, \tilde{x}'_{n,k}) = \Pr(D_{n,j} = 1 \mid \tilde{\eta}_{n,j,k})$, which a binomial logit or probit model satisfies; additive separability of the selection function in the second step; and an exclusion restriction. To satisfy the final condition, we assume that the PMMS survey rate for the non-chosen alternative does not directly influence the rate for the chosen alternative, except via the probability of being selected. So the ARM survey rate is absent from the FRM pricing equation, and the FRM survey rate from the ARM pricing equation. We also exclude borrowers' age, age^2, and their experiences of interest rates from the second-stage pricing equations.

In the third step, we impute pairs of interest rates for each household using our selection-corrected estimates of the pricing equation coefficients, and use these predicted explanatory variables to estimate the structural-choice model in (A.3). As mentioned, the pricing equation intercept $\gamma_{0,j}$ is not identified in the two-step series estimator (A.7). However, Heckman (1990) suggests estimating it by calculating the mean or median difference between the dependent variable and the predicted value conditional on all other explanatory variables, $Rate_{n,j} - Z'_{n,j}\hat{\Gamma}_{n,j}$, using only those observations whose selection probabilities for alternative i are close to 1. Intuitively, these individuals are likely to have chosen j due to observed factors. They suffer from little selection bias, and their mean or median pricing error should be close to zero. Schafgans and Zinde-Walsh (2002) show that Heckman's intercept estimator is consistent and asymptotically normal. We estimate the intercept as the median difference within the top 10% of observations from each selected subsample, sorted by their predicted choice probabilities.

We calculate the "average selection bias" reported at the bottom of Table 4 as the mean of $\hat{g}(\hat{\tilde{\eta}}_{n,j,k}) = \widehat{\mathbb{E}}[Rate_{n,j} \mid Z_{n,j}, D_{n,j} = 1] - \widehat{\mathbb{E}}[Rate_{n,j} \mid Z_{n,j}]$. This subtracts the Heckman (1990) intercept estimator from the SPSC control function to estimate the unknown selection bias function $g(\cdot)$ in (A.6).

We obtain standard errors that account for the presence of predicted regressors in Steps 2 (the choice probabilities) and 3 (the risk-adjusted FRM and ARM rates for each borrower) by bootstrapping the entire three-step procedure 200 times.[42]

E.2 Derivation of the WRTE

The Welfare-Relevant Treatment Effect is the expected cost of choosing an FRM over an ARM for switching households, for whom experience-based learning was the determining factor in their mortgage choice. We derive its estimator (11) using the language of potential treatments and potential outcomes.

Numbering the FRM alternative as 1 and the ARM alternative as 0, every household n faces two *potential outcomes*: mortgage payments $Y_{n,1}$ under the FRM and mortgage payments $Y_{n,0}$ under the ARM. The observed mortgage payments in our data is $Y_n = D_n Y_{n,1} + (1 - D_n)Y_{n,0}$, where $D_n \in \{0, 1\}$ is the mortgage choice of household n (*treatment status*). As defined in equation (A.2), the value of D_n depends on the difference in latent utility (4) between the alternatives, which depends on the value of the coefficient on interest-rate experiences, δ_{ie}.

Let $D_n(\delta_{ie})$ be the potential choice (*potential treatment*) individual n would make, given experience coefficient δ_{ie} (*assignment*). We can rewrite the choice observed in our data as

$$D_n = \int A(ð) D_n(\delta_{ie}) \, \mathrm{d}\delta_{ie} \, , \tag{A.8}$$

where $A(\cdot) = \mathbb{I}\{\delta_{ie} = \cdot\}$ and ð is the true value of δ_{ie} in the population, representing the additional weight placed on i^e in the household's interest-rate forecast (3) beyond the full-information Bayesian optimum. The household's actual choice is $D_n(ð) \in \{0, 1\}$; and the welfare-relevant counterfactual is the choice the household would have made in the same

[42] Angelis et al. (1993) and Hahn (1995) show that the bootstrap consistently approximates the distribution of LAD-type estimators, as in Step 2.

choice situation if placing no additional weight on personal experiences: $D_n(0) \in \{0, 1\}$. If $D_n(ð) = D_n(0)$, then "assignment," i.e., experience-based learning, was irrelevant and did not influence "treatment status," i.e., the mortgage choice. If $D_n(ð) \neq D_n(0)$, then the household would switch out of an FRM into an ARM under the counterfactual "assignment."[43]

Using this notation, the expected financial cost for switching households is

$$WRTE \coloneqq \mathbb{E}[Y_{n,1} - Y_{n,0} \mid D_n(ð) = 1, D_n(0) = 0] \,, \tag{A.9}$$

i.e., the expected difference between FRM and ARM payments for households that chose an FRM because they overweighted their interest-rate experiences. Positive numbers represent that overweighting was costly, and negative numbers that it was beneficial. The conditioning set restricts us to the subset of mortgagors for whom experience-based learning was the determining factor in their mortgage choice. In reference to Heckman and Vytlacil (2007)'s formulation of the "policy-relevant treatment effect" (PRTE), using the same weighted average that we derive next, we call this the *Welfare-Relevant Treatment Effect* (WRTE).

We cannot directly estimate equation (A.9) because we do not observe households' counterfactual choices $D_n(0)$. However, Bayes' rule lets us rewrite (A.9) as

$$\mathbb{E}\left[\Delta Y_n \mid D_n(ð) = 1, D_n(0) = 0\right] = \int \Delta y \cdot f(\Delta y \mid D_n(ð) = 1, D_n(0) = 0) \, \mathrm{d}\Delta y \tag{A.10}$$

$$= \frac{\int \Delta y \cdot h(D_n(ð) = 1, D_n(0) = 0 \mid \Delta y) f(\Delta y) \, \mathrm{d}\Delta y}{g(D_n(ð) = 1, D_n(0) = 0)} \,. \tag{A.11}$$

Equation (A.10) gives the definition of a conditional expectation, using $f(\Delta y \mid \cdot)$ to notate the density of payment differences Δy conditional on the household being a switcher. Because we do not observe counterfactual choices, this conditional density is unknown and cannot be estimated directly. The next line (A.11) uses Bayes' rule to replace this with estimable functions. The probability mass function, $h(\cdot \mid \Delta y)$, gives the probability that a household facing payment difference Δy would switch to an ARM were it not for the presence of

[43] Households only switch in one direction because we model $\Pr(D_n = 1 \mid \delta_{ie} i^e)$ as a logit function, so that expected household choice is monotonic in $\delta_{ie} i^e$, and $i^e > 0$.

personal interest-rate experiences in its choice function. Multiplication by the unconditional density $f(\Delta y)$ indicates that we need to integrate over all payment differences Δy according to how often they occur in the population; and division by the unconditional mass function g ensures that the densities integrate to 1. Thus, we no longer need to know households' counterfactual *choices*, merely their switching *probabilities*.

Intuitively, equation (A.11) is the weighted average difference in FRM versus ARM mortgage payments, using households' switching probabilities as weights. We calculate the probability h_n that a household is a switcher by comparing two choice probabilities: the "true" probability that uses all the population coefficient values, and a "counterfactual" probability that sets $\delta_{ie} = 0$ but uses all the other population coefficients:

$$\begin{aligned} h_n &= h(D_n(ð) = 1, D_n(0) = 0 \mid \Delta y) \\ &= \Pr(D_n = 1 \mid \delta_{ie} = ð, \Delta y) - \Pr(D_n = 1 \mid \delta_{ie} = 0, \Delta y)\,, \end{aligned} \tag{A.12}$$

corresponding to equation (10) in the paper. To construct an estimator $\hat{h}_n$ of h_n, we can replace the population choice probabilities with predicted values using the logit function estimates in Table 3 or 5; the population experience coefficient ð with an estimate, $\hat{\delta}_{ie}$, from the reduced-form or the structural choice model; and the actual FRM–ARM payment difference Δy_n with predicted differences $\Delta \hat{y}_n$ obtained from the selection-corrected pricing equations reported in Table 4.

Drawing a random sample from the population distribution $f(\Delta y)$, and replacing ð, h_n, and Δy_n in (A.11) with the consistent estimators $\hat{\delta}_{ie}$, $\hat{h}_n$, and $\Delta \hat{y}$ just described, gives our estimator of the WRTE (corresponding to (11) in the paper):

$$\widehat{WRTE} \equiv \widehat{\mathbb{E}}\left[Y_{n,1} - Y_{n,0} \mid D_n(ð) = 1, D_n(0) = 0\right] \tag{A.13}$$

$$:= \sum_{n=1}^{N} \Delta \hat{y}_n \cdot \frac{\hat{h}_n}{\sum_n \hat{h}_n} \tag{A.14}$$

$$= \sum_{n=1}^{N} \Delta \hat{y}_n \cdot \left(\frac{\widehat{\Pr}(D_n(\hat{\delta}_{ie}) = 1 \mid \Delta \hat{y}_n) - \widehat{\Pr}(D_n(0) = 1 \mid \Delta \hat{y}_n)}{\sum_n \left(\widehat{\Pr}(D_n(\hat{\delta}_{ie}) = 1 \mid \Delta \hat{y}_n) - \widehat{\Pr}(D_n(0) = 1 \mid \Delta \hat{y}_n) \right)} \right). \tag{A.15}$$

Note that the WRTE (and PRTE) differ from standard objects reported in the treatment literature. For example, an Average Treatment Effect (ATE) is calculated as the *unweighted* average of the difference in expected payments,

$$\mathbb{E}[Y_n \mid \delta_{ie} = \eth] - \mathbb{E}[Y_n \mid \delta_{ie} = 0] = \sum_{j=0}^{1} \Pr(D_n(\eth) = j) \cdot Y_{n,j} - \sum_{j=0}^{1} \Pr(D_n(0) = j) \cdot Y_{n,j} ,$$

using the actual versus the counterfactual choice probabilities.[44]

E.3 Modeling Refinancing Behavior

Optimal Refinancing. Agarwal, Driscoll, and Laibson (2013), hereafter ADL, provide a closed-form solution for this threshold. We use their square-root rule approximation to the optimal threshold:

$$OT_{n,t} \approx -\sqrt{\frac{\sigma\kappa}{M_{n,t}(1-\tau)}}\sqrt{2(\rho + \lambda_{n,t})} , \tag{A.16}$$

where σ is the annualized standard deviation of movements in the FRM rate, κ is the fixed cost of refinancing, M is the outstanding mortgage balance, τ is the household's marginal tax rate, ρ is the household's intertemporal discount rate, and λ is the Poisson arrival rate of exogenous prepayment events. We follow ADL in parameterizing $\sigma = 0.0109$, $\kappa = \$2000$, and $\rho = 0.05$; and we continue to set the marginal tax rate $\tau = 0.25$. (ADL use the next bracket up, 28%.) The mortgage prepayment process parameterized by $\lambda_{n,t}$ is derived from three exogenous sources of principal repayment:

$$\lambda_{n,t} = \mu + \frac{i_n}{\exp(i_n(T-t)) - 1} + \pi . \tag{A.17}$$

The first term, μ, represents the hazard of moving and selling the house; this could in principle vary across households, but we follow ADL and set $\mu = 0.10$ (corresponding to an expected residency of $1/\mu = 10$ years). The second term represents the annual scheduled repayment of principal for a self-amortizing FRM carrying interest rate i_n with $T - t$ years remaining. The third term represents declines in the real value of future mortgage payments

[44] By this logic, our WRTE is a Local Average Treatment Effect for the subset of the population for whom assignment is deterministic.

due to inflation. This could also vary over time with actual inflation, but for simplicity we set $\pi = 0.04$ (the mean CPI inflation rate over 1960–2013).

Expected Refinancing. To calculate a household's expected mortgage payments, we borrow estimates from Andersen et al. (2015) that describe the probability of refinancing as a function of the "incentive to refinance" embedded in the difference between the optimal threshold and the actual rate differential. Their baseline estimate of the probability that a household n will refinance in month m in year t is

$$\Pr(\mathit{Refi}_{n,t,m} \mid i_0) = \Phi\left(-1.921 + \exp(-1.033) \times (OT_{n,t} - (i_{n,t} - i_0))\right) , \tag{A.18}$$

where i_0 is the interest rate on the outstanding fixed-rate mortgage and $i_{n,t}$ is the interest rate on a new mortgage issued if the household refinances in year t.[45] We convert from a monthly to an annual horizon by assuming that monthly refinancing events are i. i. d. within a year: $\Pr(\mathit{Refi}_{n,t} \mid i_0) = 1 - (1 - \Pr(\mathit{Refi}_{n,t,m} \mid i_0))^{12}$. The refinancing probability may be interpreted as a transition probability between two "states": the state of holding a year-$(\mathit{OrigYr}_n + s)$ mortgage and the state of holding a year-$(\mathit{OrigYr}_n + t)$ mortgage, where s and t denote the number of years between origination and the previous refinancing or today, respectively. If i_0 is the rate $s \geq 0$ years after origination, and today is $t > s$ years after origination, then

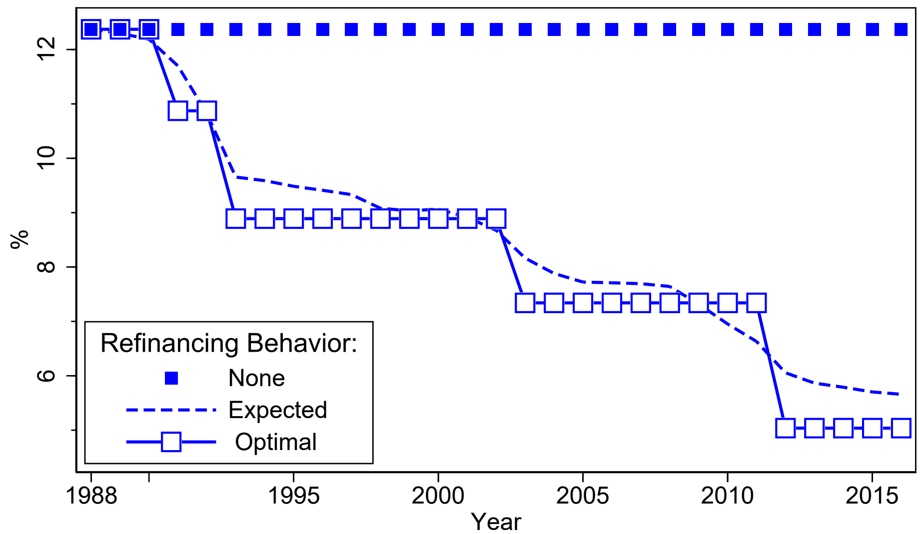
$$P_n(S_t = t \mid S_{t-1} = s) \coloneqq \Pr(\mathit{Refi}_{n,\mathit{OrigYr}_n+t} \mid i_0 = i_{n,\mathit{OrigYr}_n+s}) \cdot \mathbb{I}\{s < t\} \, . \tag{A.19}$$

$S_t \in \{0, 1, 2, ..., t\}$ denotes the household's current, time-t "state," i.e., the time of the most recent refinancing. To obtain the set of unconditional probabilities that, at time t, household n will hold a mortgage last refinanced at time s, $\{P_n(S_t = s), 0 \leq s \leq t \leq 29\}$, we begin with the initial condition that $P_n(S_0 = 0) = 1$ and solve forward iteratively.[46]

[45] From Andersen et al. (2015), Table 9, col. 1, based on a sample of Danish households from 2008 to 2012.

[46] The calculations also need to keep track of the household's outstanding mortgage balance at the beginning of each year. This state variable depends on the entire path of prior interest rates. There are $2^{29} \approx 500$ million such paths for every mortgage. To simplify matters, we assume that the timing of principal repayment in the "Expected Refinancing" case is the same as in the "Optimal Refinancing" case.

Figure A.3. FRM Rate for Mortgage ID 500



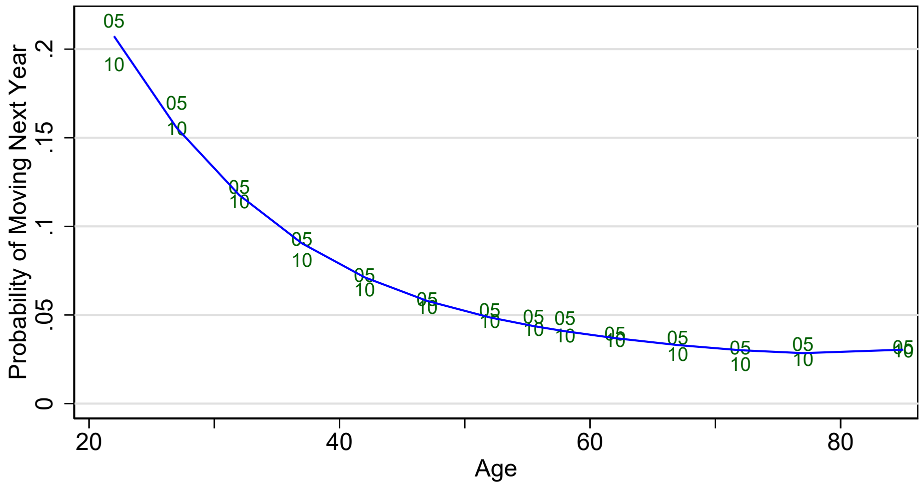
Notes. Date from the 1991 RFS. The expected FRM rate for a household n is integrated over all potential time-t rates using the time-t state probability distribution: $E[i_{n,t}] = \int_{1 \leq s \leq t} i_{n,s} P_n(S_t = s)\,\mathrm{d}s$.

Illustration. Figure A.3 illustrates these calculations for one of our sample households. Optimal refinancing occurs in years 4, 6, 16, and 25 (= 1991, 1993, 2003, and 2012). "Expected" rates, integrating over all potential rates using the time-t state probability distribution, sometimes track "optimal" rates with a lag (1993–2001), indicating delayed refinancing behavior in expectation, and sometimes with a lead (2010–11), indicating refinancing too early in expectation—see the references in Section 5.2.

E.4 Estimating Borrower Mobility

Moving Probabilities Based on Age. To estimate household moving probabilities, we obtain CPS-ASEC five-year geographic mobility estimates for the time periods 2000–05 and 2005–10 from the Census Bureau. We choose these time periods in order to capture both an expansion and a recession, so that we may smooth over business-cycle frequency variation in mobility rates. The Census's survey question asks respondents whether they lived in the same house or apartment five years ago, and classifies movers by type of move (within county, state, division, region, or from abroad). Since even a local move necessitates terminating the mortgage, we use the total mobility rate. The data does not break out renters versus homeowners, so our mobility-rates estimates are based on the entire population.

Figure A.4. Age and Mobility



Notes. The data source is the CPS ASEC from 2005 and 2010. Fitted values are calculated using fourth-order polynomial function of age.

We convert five-year moving frequencies into one-year (ex-ante) probabilities as follows. First, since respondents are grouped into five-year age ranges, we code individuals' ages at the interval medians. So for example, individuals in the 35–39 year interval are coded as 37 years old today, and as 32 years old five years ago. We further top-code the highest interval (85+ years) at 85, and we drop respondents who were minors five years ago (i.e., aged less than 22 years at the time of the survey). We then convert the five-year moving probabilities to one-year moving probabilities by using an "independent-increments" (Poisson) assumption:

$$\text{MoveProb}_a^{1y} \equiv 1 - (1 - \text{MoveProb}_a^{5y})^{1/5} = 1 - \left(\frac{N_{a+5}(\text{Nonmovers})}{N_{a+5}(\text{Total})}\right)^{1/5},$$

where y is year(s), a an age bracket, and $N_a(\cdot)$ the number of individuals in age bracket a in the CPS data. We plot these one-year moving probabilities in Figure A.4. Mobility declines with age, leveling off in the mid-to-late 40s, and increasing again slightly in the late 80s.

We model the relationship between mobility and age by regressing one-year moving rates against a fourth-order polynomial in householder age:

$$\widehat{\text{MoveProb}}^{1y}(age) = \underset{(0.077)}{0.696} - \underset{(0.007)}{0.0355} \times age + \underset{(0.0002)}{0.000752} \times age^2$$
$$- \underset{(2.80 \cdot 10^{-6})}{7.40 \cdot 10^{-6}} \times age^3 + \underset{(1.30 \cdot 10^{-8})}{2.80 \cdot 10^{-8}} \times age^4 \,. \tag{A.20}$$

(Standard errors are in parentheses.) We finally use these coefficients to estimate the probability that a householder of age a today will still be in the house after T years:

$$\text{StayProb}(a, T) = \prod_{s=0}^{T-1} \left(1 - \widehat{\text{MoveProb}}_{1y}(a + s)\right) \,. \tag{A.21}$$

Moving Probabilities Based on Discount Points Paid. Discount points represent a trade-off between an upfront cost and a future benefit. Each discount point costs 1% of the amount borrowed, P, so the upfront cost of purchasing p points is $0.01pP$. Each discount point buys approximately a 25 basis point reduction in the mortgage interest rate. The exact point-interest rate schedule may vary by bank and over time, but inspection of our data suggests that a quadratic function is a good description of the average schedule: $r(p) = r_0 - 0.0027p + 0.0002p^2$. This is the same order of magnitude that Brueckner (1994) finds for the early 1990s.

Common investment advice is to purchase enough points such that, over the expected tenure in the house, the lower monthly payments just offset the upfront cost.[47] However, households might pay fewer points if they are risk averse or face liquidity constraints at the time of mortgage origination. Moreover, Agarwal et al. (2017) show that in practice borrowers do not pay points optimally, calling into question the rational interpretation of borrowers' empirically-observed menu choices. In our data, only 16.5 percent of households pay discount points, with a median of 2 points paid. Nevertheless, we check the robustness of our results to utilizing discount points for the estimation of geographic mobility.

[47] Cf. https://www.investopedia.com/articles/pf/06/payingforpoints.asp or https://www.bankrate.com/finance/mortgages/mortgage-points.aspx. In theory, a risk-neutral household should purchase points until the expected tenure exactly equals the break-even time it will take to recover the upfront payment.

To estimate moving probabilities, we calculate the break-even horizon τ^* for each household, given the number of points paid, predicted future interest rate savings, and discount rate d:

$$\begin{aligned}\text{Upfront Cost} &= PV(\text{Future savings}) \\ 0.01pP &= \sum_{t=1}^{\tau^*} \frac{M(r_0, P) - M(r(p), P)}{(1+d)^t}\,,\end{aligned} \tag{A.22}$$

where $M(r, P)$ is the per-period payment for a 30-year FRM with face value P and interest rate r. The right-hand side of (A.22) is a τ^*-period annuity, so rearranging the standard annuity formula and taking logs gives

$$\tau^* = \frac{-\log\left(1 - \frac{0.01pP}{\Delta M/d}\right)}{\log(1+d)}\,. \tag{A.23}$$

If households are risk-neutral and face no liquidity constraints, then they will expect to reside in the house for exactly τ^* periods.

We solve for each household's break-even horizon in months using (A.23) given the number of points they actually paid, their Scenario 1, 2, or 3 predicted FRM rate, $r(p)$, and an annual discount rate of 8%.[48] We then map expected tenure to a moving probability distribution by assuming a constant hazard rate of moving (Poisson), so that years until moving follow a negative exponential distribution, $\tau \sim N.E.(\lambda)$, with intensity parameter $\lambda = 1/E[\tau] = 1/\tau^*$. Alternatively, to model a hazard rate that decreases with time due to community attachment (Dynarski 1985, 1986; Quigley 1987), we let moving times follow a Weibull(λ, α) distribution with shape parameter $\alpha = 0.7$.[49] Finally, we allow for the possibility that individuals choose fewer than the optimal number of points due to risk aversion or liquidity constraints by fitting the intensity parameter to the median, rather than the mean: $F_\lambda^{-1}(\tau^*) = 0.5$.

[48] We impute expected tenure for households not buying points by calculating τ^* for a representative household over a grid of values for p between 0.5 and 6.5, and for r_0 between 5 and 15%, then running a "kitchen-sink" regression of τ^* on r_0, r_0^2, p, p^2, r_0p, and r_0p^2. This gives $\widehat{\mathbb{E}}[\tau^* \mid p = 0] = 112.3 - 772.2r_0 + 2720r_0^2$ in months. Applied to our data, the mean imputed value of τ^* is 62 months for households not buying points, versus 81 months for households buying points using (A.23).

[49] The negative exponential distribution equals the Weibull distribution with $\alpha = 1$.

Table A.7 reports the estimation results. We see significantly lower estimates of median tenure relative to our previous age-based calculations (bottom row of each panel). This discrepancy reflects that most households do not pay any discount points. The discrepancy is exacerbated under the Weibull distribution (column 4) and ameliorated when we fit each household's break-even horizon to the median rather than the mean (columns 3 and 5). Ignoring these concerns, we estimate the WRTE to be somewhat lower using the points-paid methodologies: under expected refinancing behavior and Scenario 3 interest rates, between $11 and 15 thousand, as compared to $19 thousand using age-based estimates of mobility.

Table A.7: Moving Probabilities Based on Discount Points Paid

	(1)	(2)	(3)	(4)	(5)
P(Moving) based on:	*Age*	*Discount Points Paid*			
Distribution:		Neg. Exp. (λ)		Weibull(λ, 0.7)	
Break-Even Year (τ*):		τ*=E[τ]	F(τ*)=0.5	τ*=E[τ]	F(τ*)=0.5
	Scenario 1: Primary Mortgage Market Survey rates				
After-tax PDV [in $]:					
No Refi	12,547	6,389	8,522	6,031	9,503
Expected Refi	7,667	4,982	6,019	4,545	6,219
Optimal Refi	6,365	4,262	5,068	3,915	5,228
Av. Median Tenure (years)	12.3	4.9	6.7	3.6	6.7
	Scenario 2: Risk-adjusted rates, seniority-adjusted ARM margins				
After-tax PDV (all in $):					
No Refi	25,915	13,819	17,846	12,792	19,378
Expected Refi	19,119	11,825	14,428	10,721	14,936
Optimal Refi	17,683	11,071	13,422	10,060	13,878
Av. Median Tenure (years)	12.3	4.7	6.3	3.6	6.3
	Scenario 3: Risk-adjusted rates and ARM margins				
After-tax PDV (in $):					
No Refi	24,767	13,195	17,038	12,250	18,542
Expected Refi	17,983	11,209	13,630	10,185	14,111
Optimal Refi	16,546	10,454	12,623	9,524	13,052
Av. Median Tenure (years)	12.3	4.7	6.3	3.6	6.3

Notes. The table reports expected additional interest paid by switching households, allowing for heterogeneity in the probability of moving based on head of household's age or discount points paid. All dollar amounts are in constant year-2000 units. Column (1) reproduces the estimation from the final column of Table 6 for comparison. In columns (2)–(5), discount points paid at time of origination are used to calculate the time to break even, τ^*, for each household, assuming an annual discount rate of $d = 8\%$ in (A.23). In columns (2) and (3), the time of moving events $\tau \sim$ Negative Exponential (λ) distribution, with λ picked to fit τ^* to the mean and median of the distribution for each household. In columns (4) and (5), the time of moving events $\tau \sim$ Weibull $(\lambda, 0.7)$ distribution, so the hazard rate of moving is decreasing over time, with λ picked to fit τ^* to the mean and median of the distribution for each household. Average median tenure is calculated as the median tenure for each household, then averaged over all switching households.

F Monte Carlo Simulation Parameters

Our simulation setup follows Campbell and Cocco (2003). We assume that inflation follows an AR(1) process, $\pi_t = \mu + \phi(\pi_{t-1} - \mu) + \epsilon_{\pi,t}$, with serially-independent innovations $\epsilon_{\pi,t} \sim \mathcal{N}(0, (1-\phi^2)\sigma_\pi^2)$. One-year log real interest rates are serially uncorrelated: $r_t = \rho + \epsilon_{r,t}$, where $\epsilon_{r,t} \sim$ indep. $\mathcal{N}(0, \sigma_r^2)$ that are mutually-independent to the inflation innovations, $\epsilon_{r,\cdot} \perp \epsilon_{\pi,\cdot}$. The short-term nominal (log) interest rate equals the real interest rate plus inflation: $y_t^1 = r_t + \pi_t$. Long-term nominal rates follow the Expectations Hypothesis with a constant term premium: $y_t^T = \frac{1}{T}\sum_{s=1}^{T}\mathbb{E}_t y_{t+s-1}^1 + \theta^T$, where $\mathbb{E}_t y_{t+s}^1 = \rho + \phi^s(\pi_t - \mu) + \mu$.

The ARM rate tracks the one-year nominal bond rate with a lower initial "teaser" premium. In year 1, the initial ARM rate is $y_1^A = y_t^1 + \theta^{A,1}$; and in years 2–30, the ARM reset rate is $y_t^A = y_t^1 + \theta^A$. The FRM rate tracks the ten-year nominal bond rate: $y_t^F = y_t^{10} + \theta^F$. Hence, the FRM–ARM spread realistically tracks the nominal bond yield spread (as documented in Appendix D).

Table A.8: Simulation Parameters

Parameter	Description	Value	Source
μ	Mean log inflation	0.038	CPI-U, 1960-2013
σ_π	Standard deviation of log inflation	0.027	CPI-U, 1960-2013
ϕ	Log inflation autoregression parameter	0.811	CPI-U, 1960-2013
ρ	Mean log real interest rate	0.02	Campbell & Cocco (2003)
σ_r	Standard deviation of log real interest rate	0.022	Campbell & Cocco (2003)
θ^{10}	Ten-year nominal term premium	0.01	Average of ten-year minus one-year constant maturity U.S. Treasury yields, 1960-2013
$\theta^{A,1}$	ARM initial premium over one-year nominal bond (year 1 only)	0.015	Average spread between PMMS initial rate and CM U.S. Treasury, 1984-2013
θ^A	ARM reset margin over one-year nominal bond (years 2-30)	0.0275	Average PMMS margin, 1987-2013
θ^F	FRM premium over ten-year nominal bond	0.017	Average spread between PMMS rate and CM U.S. Treasury, 1971-2013

Table A.8 summarizes the simulation parameters. To reflect the economic environment before and after the Great Inflation, we calibrate parameters to real-world values over all available years in 1960–2013 using the PMMS, constant-maturity U.S. Treasury data, and headline CPI. In particular, we set the term premium to $\theta^{10} = 1\%$, the FRM premium over the ten-year bond rate to $\theta^F = 1.7\%$, the initial ARM premium over the one-year bond rate to nominal $\theta^{A,1} = 1.5\%$, and the subsequent ARM premium to $\theta^A = 2.75\%$. Our parametrization does not bias in favor of either contract (cf. Table 7: the mean simulated FRM–ARM spread over all 30 years is 5 basis points). However, the ARM is calibrated to be cheaper than the FRM in year 1 but more expensive in years 2–30; so younger and more mobile households should realistically benefit from choosing the ARM.[50]

G Empirical Framework Derivations

In Section 6.2, we argue that we can place bounds on the true effect size of the individual inflation forecast on mortgage choice in equation (19) by comparing $\hat{\delta}_{1,OLS}$ and $\hat{\delta}_{1,IV}$. We show this more carefully here.

Recall first that the just-identified (for ease of exposition) IV estimator of $y_i = x_i'\beta + \upsilon_i$ with positively-correlated instruments z_i takes the form

$$\hat{\beta}_{IV} = \left(\frac{1}{N}\sum\nolimits_i z_i x_i'\right)^{-1}\left(\frac{1}{N}\sum\nolimits_i z_i y_i\right) \xrightarrow{p} \beta + \left(\mathbb{E}[z_i x_i']\right)^{-1}\mathbb{E}[z_i \upsilon_i]\,. \tag{A.24}$$

In OLS, the instruments and regressors are the same, $z_i \equiv x_i$. If $\mathbb{E}[z_i\upsilon_i] = 0$, then the estimator is consistent for β. Otherwise, if the moment expression $\mathbb{E}[z_i\upsilon_i]$ is positive (negative), the probability limit is greater than (less than) the structural parameter β.

Preliminary Result: Non-classical measurement error ι. The source of endogeneity in our empirical framework is measurement error in the interest rate forecast ι. This arises due to a timing discrepancy: interest rate expectations are observed after the mortgage is taken out instead of contemporaneously. Because expectations are serially correlated, the measurement error term is "non-classical" and is negatively correlated with the level of the initial forecast: $\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] < 0$. We show this first, as a preliminary result; then we use this to analyze the probability limits of the OLS and IV estimators given by (A.24).

Letting L be the lag operator, observe that personal interest-rate experiences (5) are

[50] By contrast, Campbell and Cocco (2003) use the same term premium, a ten-basis-point higher FRM premium of 1.8%, and a significantly lower ARM markup of 1.7% for the *entire lifetime* of the mortgage, implying that the ARM is *cheaper* than the FRM in expectation. As the authors acknowledge, their ARM premium "may be biased downward" by not treating teaser and reset rates separately (p. 1466).

obtained by applying an absolutely-summable linear filter $w_{s,t}(L) = \left(\sum_{j=0}^{t-s}(t-s-j)\right)^{-1} \times \sum_{k=0}^{t-s}(t-s-k)L^k$ to a stationary AR(1) process: $i^e_{n,t} = w_{s,t}(L)i_t$. In fact, $i^e_{n,t}$ is a weighted sample mean, and it follows that $\text{Var}(i^e_{n,t+1}) < \text{Var}(i^e_{n,t})$, $\lim_{\to\infty}\text{Var}(i^e_{n,t}) = 0$, and $i^e_{n,t} \xrightarrow{p} \mathbb{E}[i]$.

Further, interest-rate experiences may be written recursively as

$$i^e_{n,t+1} = \phi_{t+1}i^e_{n,t} + (1-\phi_{t+1})i_{t+1}\,, \tag{A.25}$$

$$\text{so } \Delta i^e_{n,t+1} = (\phi_{t+1}-1)(i^e_{n,t} - i_{t+1})\,, \tag{A.26}$$

where $\phi_{t+1} = t/(t+2)$ for an individual born at $s = 0$.

Equation (18) states that the *ex post* interest rate forecast differs from the *ex ante* forecast by three factors: the evolution of personal interest-rate experiences Δi^e, the mean-reverting component of the forecast error term ξ, and a new forecast innovation ν that is white noise. Given this, the change in the interest rate forecast $\Delta\iota$ in (17) is not pure white noise:

$$\begin{aligned}
\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] &= \mathbb{E}[(\alpha_{0,t} + \alpha_1 i^e_{n,t} + \xi_{n,t})(\alpha_1\Delta i^e_{n,t+1} + (\varphi-1)\xi_{n,t} + \nu_{t+1})] \\
&= \alpha_{0,t}\left(\alpha_1 \underbrace{\mathbb{E}[\Delta i^e_{n,t+1}]}_{=0 \text{ by (A.26)}} + \underbrace{\mathbb{E}[(\varphi-1)\xi_{n,t} + \nu_{t+1}]}_{=0 \text{ by (13) and (14)}}\right) \\
&\quad + \alpha_1\left(\alpha_1\mathbb{E}[i^e_{n,t}\Delta i^e_{n,t+1}] + (\varphi-1)\underbrace{\mathbb{E}[i^e_{n,t}\xi_{n,t}]}_{=0 \text{ by (16)}} + \underbrace{\mathbb{E}[i^e_{n,t}\nu_{t+1}]}_{=0 \text{ by (14)}}\right) \\
&\quad + \alpha_1 \underbrace{\mathbb{E}[\xi_{n,t}\Delta i^e_{n,t+1}]}_{\substack{=-(\phi_{t+1}-1)\mathbb{E}[\xi_{n,t}i_{t+1}] \text{ by (A.26) and (16)} \\ =0 \text{ by (12), (14), and (16)}}} + (\varphi-1)\mathbb{E}[\xi^2_{n,t}] + \underbrace{\mathbb{E}[\xi_{n,t}\nu_{t+1}]}_{=0 \text{ by (14)}} \\
&= \alpha_1^2 \underbrace{\mathbb{E}[i^e_{n,t}\Delta i^e_{n,t+1}]}_{<0} + (\varphi-1)\mathbb{E}[\xi^2_{n,t}] < 0\,.
\end{aligned} \tag{A.27}$$

By the Cauchy-Schwarz inequality,

$$Cov(i^e_{n,t+1}, i^e_{n,t}) \leq SD(i^e_{n,t+1})SD(i^e_{n,t}) < SD(i^e_{n,t})^2 = Var(i^e_{n,t})\,. \tag{A.28}$$

Add $(\mathbb{E}[i^e])^2$ to both sides to get that $\mathbb{E}[i^e_{n,t}i^e_{n,t+1}] < \mathbb{E}[(i^e_{n,t})^2]$, or $\mathbb{E}[i^e_{n,t}\Delta i^e_{n,t+1}] < 0$. So, (A.27) is negative, as we have claimed.

For further intuition, use (A.26) to rewrite the final line of (A.27) as

$$\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] = (\phi_{t+1} - 1)\alpha_1^2\mathbb{E}[(i^e_{n,t})^2 - i^e_{n,t}i_{t+1}] + (\varphi - 1)\mathbb{E}[\xi^2_{n,t}]\,.$$

If it were the case that $\phi_{t+1} = 1$ and $\varphi = 1$, then the interest rate forecast would be a random walk with white noise innovations ν and $\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] = 0$. However, because $0 \leq \varphi < 1$ and $0 \leq \phi_{t+1} < 1$, the forecast ι is serially correlated, so the change in the forecast $\Delta\iota$ is negatively correlated with the level of the lagged forecast.

Result 1: Probability limit of OLS. Suppose that we were to ignore the presence of measurement error and naïveley run an OLS-like regression of (19). Consistency of this estimator relies upon the orthogonality condition $\mathbb{E}[\iota_{n,t+1}u^*_{n,t}] = 0$. Expanding the moment expression gives us

$$\begin{aligned}
\mathbb{E}[\iota_{n,t+1}u^*_{n,t}] &= \mathbb{E}[\iota_{n,t+1}u_{n,t}] - \delta_1\mathbb{E}[\iota_{n,t+1}\Delta\iota_{n,t+1}] \\
&= \underbrace{\alpha_1}_{>0}\underbrace{\mathbb{E}[i^e_{n,t+1}u_{n,t}]}_{\text{ambig.}} - \underbrace{\delta_1}_{>0}\underbrace{\Big(\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] + \mathbb{E}[\Delta\iota^2_{n,t+1}]\Big)}_{\geq 0} \neq 0 \qquad \text{(A.29)}
\end{aligned}$$

in general. (We show how to derive the second line below.) For comparison, in a classical errors-in-variables setting, the first and second expectation terms in the final line would drop out, leaving $\mathbb{E}[\iota_{n,t+1}u^*_{n,t}] = -\delta_1\mathbb{E}[\Delta\iota^2_{n,t+1}] < 0$, since $\delta_1 > 0$. The mis-measured regressor $\iota_{n,t+1}$ would be negatively correlated with the composite error term, leading to attenuation bias in the coefficient estimates.

However, (A.29) contains two additional terms. First, since $\mathbb{E}[\iota_{n,t}\Delta\iota_{n,t+1}] < 0$, adding this term attenuates the attenuation bias. Using the Cauchy-Schwarz inequality and the fact that ι is serially-correlated, the entire expression in parentheses remains positive, so the magnitude of bias is smaller but the direction remains negative. Second, $\mathbb{E}[i^e_{n,t+1}u_{n,t}]$ will be nonzero if $\mathbb{E}[i_{t+1}u_{n,t}] \neq 0$, i.e., if future interest rates are predictable using any unobserved or omitted factors affecting current mortgage choice. Empirically, the nationwide FRM share in year t is negatively correlated with interest rates experiences of mortgage originators in year

$t+1$.[51] This would suggest $\mathbb{E}[i^e_{n,t+1}u_{n,t}] < 0$, and since $\alpha_1 > 0$, makes the entire expression (A.29) more negative and the attenuation bias more severe.

Derivation of the OLS moment expression. To derive the second line of (A.29), we use (3) and (13) to expand $\iota_{n,t+1} = \alpha_{0,t+1} + \alpha_1 i^e_{n,t+1} + (\varphi\xi_{n,t} + \nu_{n,t+1})$ and simplify the first right-hand term:

$$\begin{aligned}
\mathbb{E}[\iota_{n,t+1}u_{n,t}] &= \alpha_{0,t+1}\underbrace{\mathbb{E}[u_{n,t}]}_{=0 \text{ by } (14)} + \alpha_1\mathbb{E}[i^e_{n,t+1}u_{n,t}] + \varphi\underbrace{\mathbb{E}[\xi_{n,t}u_{n,t}]}_{=0 \text{ by } (15)} + \underbrace{\mathbb{E}[\nu_{n,t+1}u_{n,t}]}_{=0 \text{ by } (14)} \\
&= \alpha_1\mathbb{E}[i^e_{n,t+1}u_{n,t}]\,,
\end{aligned} \tag{A.30}$$

then rewrite the second right-hand term as $\mathbb{E}[\iota_{n,t+1}\Delta\iota_{n,t+1}] = \mathbb{E}[(\iota_{n,t} + \Delta\iota_{n,t+1})\Delta\iota_{n,t+1}]$.

Result 2: Probability limit of IV. Now, suppose we were to address the endogeneity between $\iota_{n,t+1}$ and $u^*_{n,t}$ via instrumental variables. A common empirical technique in rational expectations models where the researcher only observes an *ex post* outcome is to use the lagged value of some variable as an instrument (e.g., Hall (1988) on consumption, Yogo (2004) on real interest rates). The structure of our two-equation model (2) and (3) suggests such an instrument. Contemporaneous, time-t interest-rate experiences $i^e_{n,t}$ are correlated with the contemporaneous, time-t interest rate forecast $\iota_{n,t}$, and they have no direct effect on mortgage choice, except through their impact on an individual's interest rate forecast. However, we need the instrument to be orthogonal not only to the structural error term u in (2), but to the composite error term u^* in the feasible regression equation (19). Expanding the exogeneity moment expression,

$$\begin{aligned}
\mathbb{E}[i^e_{n,t}u^*_{n,t}] &= \mathbb{E}[i^e_{n,t}u_{n,t}] - \delta_1\mathbb{E}[i^e_{n,t}\Delta\iota_{n,t+1}] \\
&= \quad 0 \quad - \underbrace{\delta_1\alpha_1}_{>0}\underbrace{\left(\mathbb{E}[i^e_{n,t}i^e_{n,t+1}] - \mathbb{E}[(i^e_{n,t})^2]\right)}_{<0} > 0\,.
\end{aligned} \tag{A.31}$$

$\delta_1 > 0$ and $\alpha_1 > 0$ by economic theory, and the sign of the term in parentheses is found by

[51] Using the most recent SCF survey to calculate the FRM share in every origination year between 1987–2013, $\rho = -0.54$.

applying the Cauchy-Schwarz inequality, as we show below.

Derivation of the IV moment expression. To derive the second line of (A.31), consider in turn the two terms on the right-hand side of the first line. Theory tells us that contemporaneous interest-rate experiences have no direct effect on mortgage choice, except through their impact on an individual's interest rate forecast:

$$\mathbb{E}[i^e_{n,t} u_{n,t}] = \mathbb{E}[\alpha_1^{-1}(\iota_{n,t} - \alpha_{0,t} - \xi_{n,t}) u_{n,t}] = 0 \tag{A.32}$$

by (14), (15), and (16). It remains to evaluate

$$-\delta_1 \mathbb{E}[i^e_{n,t} \Delta\iota_{n,t+1}] = -\delta_1 \mathbb{E}[i^e_{n,t}(\alpha_1 \Delta i^e_{n,t+1} + (\varphi - 1)\xi_{n,t} + \nu_{t+1})] \tag{A.33}$$

$$= -\delta_1 \left(\alpha_1 \mathbb{E}[i^e_{n,t} \Delta i^e_{n,t+1}] + (\varphi - 1) \underbrace{\mathbb{E}[i^e_{n,t}\xi_{n,t}]}_{=0 \text{ by } (15)} + \underbrace{\mathbb{E}[i^e_{n,t}\nu_{t+1}]}_{=0 \text{ by } (14)} \right) \tag{A.34}$$

$$= -\underbrace{\delta_1 \alpha_1}_{>0} \underbrace{\left(\mathbb{E}[i^e_{n,t} i^e_{n,t+1}] - \mathbb{E}[(i^e_{n,t})^2] \right)}_{<0} > 0\,. \tag{A.35}$$

$\delta_1 > 0$ and $\alpha_1 > 0$ by economic theory, and the sign of the term in parentheses is found by the Cauchy-Schwarz inequality (A.28). This gives the second line of (A.31).

Result 3: Feasible first-stage regression. Plugging (17) into (3) gives

$$\iota_{n,t+1} = \alpha_{0,t} + \alpha_1 i^e_{n,t} + \underbrace{(\xi_{n,t} + \Delta\iota_{n,t+1})}_{\xi^*_{n,t}} \tag{A.36}$$

The feasible first-stage regression (A.36) adds measurement error to the dependent variable rather than an independent variable. If the interest rate forecast were a random walk, then $\Delta\iota$ would be random noise and OLS would be consistent.

The OLS orthogonality expression for the first-stage feasible regression (A.36) is

$$\begin{aligned} \mathbb{E}[i^e_{n,t}\xi^*_{n,t}] &= 0 + \mathbb{E}[i^e_{n,t}\Delta\iota_{n,t+1}] \\ &= \left(\mathbb{E}[i^e_{n,t} i^e_{n,t+1}] - \mathbb{E}[(i^e_{n,t})^2] \right) < 0\,, \end{aligned} \tag{A.37}$$

by the same argument as equations (A.33) to (A.35). So, the probability limit of the OLS estimator of α_1 in (A.36) is attenuated, as we saw in the "All Mortgages" versus "New

Mortgages" columns of Table 9. Moreover, this is easily resolved by using the "correct" regressor $i^e_{n,t+1}$ so there is no timing discrepancy.

H Robustness Check: Supply-Side Constraints

Table A.9: Supply-Side Constraints

	High LTI Subsample	Low LTI Subsample	Full Sample
	(1)	(2)	(3)
Freddie Mac PMMS FRM	-3.935***	-3.305***	-3.914***
index rate (%)	(1.18)	(1.18)	(0.83)
Freddie Mac PMMS ARM	0.962**	0.903**	1.000***
initial rate index (%)	(0.45)	(0.46)	(0.32)
Interest-Rate Experiences (%)	0.085	0.288**	0.155*
	(0.12)	(0.13)	(0.09)
Log(Income)	0.003	0.063	-0.031
	(0.04)	(0.04)	(0.06)
Age	0.018	0.016	0.015
	(0.02)	(0.03)	(0.02)
$Age^2/100$	-0.015	-0.008	-0.011
	(0.02)	(0.03)	(0.02)
Number of Choice Situations	6,965	6,966	13,931
Pseudo R2	0.092	0.047	0.073
$-\beta_{\pi, FRM} / \beta_{Rate, FRM}$	0.022	0.087*	0.040*
(S.E. by delta method)	(0.030)	(0.049)	(0.024)
Origination year FE	YES	YES	YES
Mortgage controls	YES	YES	YES
Socidemographic controls	YES	YES	YES
5^{th}-order polynomial in LTI			YES

Notes. This table reports binomial logit coefficient estimates of choice between FRM, and ARM in the 1991 and 2001 RFS for mortgages originated $\leq$ 6 years ago, for subsamples split by borrower loan-to-income (LTI) ratios above or below the sample median. The dependent variable is an indicator equal to 1 if the household took out an FRM. Mortgage controls are Refi dummy, Junior Mortgage dummy, Nonconventional dummy, Loan / CLL, Jumbo dummy, and Points Paid. Sociodemographic controls are First-time Owner dummy, Joint Owners dummy, and Rural county dummy. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Throughout the analysis, we take the supply side as fixed (i.e., the spread between FRM and ARM rates does not vary when households make counterfactual choices), and we assume that all borrowers have a choice between the FRM and ARM. However, lenders might impose constraints on some borrowers. Borrowers with high loan-to-income (LTI) ratios may face debt servicing constraints and need to get an ARM in order to qualify for a mortgage loan at all, or, conversely, they may not be offered an ARM due to income risk. Borrowers with low LTI ratios are more likely to have "free choice" between the two contract types.

To address supply-side confounds, we test whether our results persist in the subsample of unconstrained borrowers with low LTIs. In Table A.9, we re-estimate the reduced-form binomial choice model separately on above- and below-median LTI subsamples. We that estimated experience effect is even stronger in the unconstrained, low-LTI subsample (column 2). Among high-LTI borrowers, instead, who might not have a choice between the alternatives, interest-rate experiences play a weaker and insignificant role (column 1). As an additional test, we estimate the choice model on the full sample while flexibly controlling for the possibility of borrower constraints by including a fifth-order polynomial in LTI, in column 3. This does not substantially affect the coefficient on lifetime interest-rate experiences (cf. Table 3, column 5). We conclude that supply-side constraints in the mortgage lending process are not driving our results.

I Robustness Check: Experiences of Inflation and Other Interest Rates

We re-estimate our reduced-form mortgage choice model (8) with lifetime experiences of other macroeconomic variables that might plausibly influence mortgage choice, in Table A.10.

Columns (2) and (3) decompose nominal interest-rate experiences into inflation experiences and *ex post* real interest-rate experiences using the Fisher equation, $i = r_{ex\ post} + \pi$. Inflation expectations should play a role in the household's decision problem because FRM payments are fixed in nominal terms: higher inflation reduces the real value of these payments and makes the FRM more affordable, the well-known "tilt problem." The results show that the effect of inflation experiences is similar in economic and statistical significance to the baseline effect of nominal interest rate experiences, whereas we cannot reject the null that personal experiences of higher real interest rates have no effect ($p = 0.33$). This is puzzling,

Table A.10: Mortgage Choice Using Experiences of Inflation and Other Interest Rates

	(1)	(2)	(3)	(4)	(5)
Freddie Mac PMMS FRM index rate (%)	-3.586***	-3.583***	-3.592***	-3.583***	-3.600***
	(0.81)	(0.81)	(0.81)	(0.81)	(0.81)
Freddie Mac PMMS ARM initial rate index (%)	0.841***	0.840***	0.838***	0.840***	0.842***
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Interest-Rate Experiences (%)	0.159*				
	(0.08)				
Inflation Experiences (%)		0.187*			
		(0.10)			
Real Interest-Rate Experiences (%)			0.300		
			(0.31)		
Long-term Interest-Rate Experiences (%)				0.181	
				(0.11)	
Yield Curve Experiences (%)					-0.716**
					(0.30)
Number of Choice Situations	14,337	14,337	14,337	14,337	14,337
Number of Alternatives	2	2	2	2	2
Pseudo R^2	0.069	0.069	0.069	0.069	0.069
Origination year FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
$-\delta_{ie\text{, FRM}} / \beta_{\text{Rate, FRM}}$	0.044*	0.052*	0.084	0.051	-0.199**
(S.E. by delta method)	(0.025)	(0.030)	(0.088)	(0.033)	(0.094)

Notes. This table reports binomial logit coefficients from a reduced-form choice model, where the dependent variable equals 1 if the household chooses an FRM. Column (1) reproduces Table 3, column 5. Column (2) calculates the household's lifetime experiences of inflation, $\pi^e_{n,t}$ from the BLS CPI-U using equation (5). Column (3) calculates the household's lifetime experiences of *ex post* real interest rates as $r^e_{n,t} = i^e_{n,t} - \pi^e_{n,t}$. Column (4) calculates the household's lifetime experiences of long-term yields on U.S. government bonds (1798–1959 from HSUS, series Cj1192; 1960–2013 from OECD MEI), $i^e_{LT n,t}$ using equation (5). Column (5) calculates the household's lifetime experiences of the yield curve slope as $i^e_{LT n,t} - i^e_{n,t}$. Controls are the same as in Table 3, col. 5. Robust standard errors in parentheses. * p<0.10, ** p<0.05 and *** p<0.01.

as higher values of either variable should lower the real present value of FRM payments similarly. This could indicate money illusion in household decision making, or it might simply reflect that most of our variation in nominal interest-rate experiences arises from the long shadows cast by Great Inflation, when i and π rose and fell in tandem (cf. Figure 2).[52]

Columns (4) and (5) calculate household's personal experiences of two alternate nominal interest rate series, the yield on long-term US government bonds, and the slope of the yield

[52] We have re-estimated the entire analysis using inflation experiences, $\pi^e_{n,t}$, and all the main results are nearly identical.

curve. By the Expectations Hypothesis, long-term yields reflect market expectations of future short-term yields plus a term premium. We thus expect experiences of long-term interest rates to be a noisy proxy for the theoretically-relevant experiences of short-term interest rates and expectations of future short-term interest rates in equation (3). Our measure of long-term interest rates is the combined long-term government bond yield series Cj1192 from the *Historical Statistics of the United States* 2006 pre-1960 and the OECD *Main Economic Indicators* database since. The point estimate in column (4) is highly similar to our baseline short-term nominal interest rate coefficient, but it is estimated less precisely and falls short of standard significance cutoffs ($p = 0.104$).[53] Column (5) builds on the insight of Koijen et al. (2009) that the difference between expected FRM and ARM payments is approximately the long-term bond premium. Their rule-of-thumb, that households estimate the time-varying term premium as the long term Treasury rate minus the average of recent short-term Treasury rates, is absorbed by our year fixed effects. We construct households' lifetime experiences of the Treasury yield curve slope, $YC^e_{n,t} = i^e_{LT,n,t} - i^e_{n,t}$, as a within-year analogue. As expected, the coefficient on yield curve experiences is negative and significant. Households that have personally experienced periods when the yield curve was steeper are less likely to choose an FRM, consistent with them estimating a higher term premium and expecting a larger FRM–ARM payment differential.

Differences in goodness of fit between the various models are slight, as evidenced by the very similar pseudo-R^2's reported at the bottom of the table. In an unreported specification, we considered including all three components of the yield curve slope: inflation experiences, real interest-rate experiences, and long-term bond yield experiences. The coefficients on inflation experiences and long-term bond yield experiences are significantly positive and negative, respectively, indicating roles for both interest-rate expectations, as in Section 3.1, and mortgage market timing, as in Koijen et al..

[53] If the model is estimated by probit, the coefficient on long-term interest rate experiences is significant at a 10% level.

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