Inflation Experiences and Contract Choice – Evidence from Residential Mortgages*

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Abstract

We show that personal inflation experiences significantly affect consumers' choice of mortgage financing. The experience-effect hypothesis implies that individuals who have experienced higher inflation over their lives so far expect higher future inflation and thus higher nominal interest rates. As a result, they prefer fixed-rate over variable-rate financing when they would be indifferent under standard belief formation. We quantify the influence of personal inflation experiences on mortgage financing using the Census Bureau's Residential Finance Survey (RFS), which provides detailed information about borrowing households linked to contract information provided by their mortgage lenders. We estimate that, compared to the adjustable-rate alternative, one additional percentage point of experienced inflation increases a borrower's willingness to pay for a fixed-rate mortgage by 6 to 21 basis points, within a given origination year. This experience effect has a major impact on the product mix of FRMs versus ARMs: nearly one in six households would switch to an ARM if not for the impact of inflation experiences. Our simulations of counterfactual mortgage payments suggest that households who would otherwise have switched pay approximately $8,000 in year-2000, after-tax dollars for the embedded inflation protection of the FRM over their expected tenure in the house, implying significant welfare consequences.

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1 Introduction

Whether to buy a home and how to finance the purchase is one of the biggest financial decisions for many households. The dominant contract type in the United States is a 30-year, fixed-rate mortgage (FRM). Since 1982 banks also originate adjustable-rate mortgages (ARMs), whose interest rates reset periodically. Despite their greater liquidity on secondary mortgage markets, FRMs are priced at a premium over ARMs, on average 170 basis points over equivalent-risk and -term ARMs.[1] The premium reflects, at least in part, that FRMs provide insurance against nominal interest rate fluctuations. However, when analyzing the choice between FRMs and ARMs in a lifecycle consumption model with borrowing constraints, Campbell and Cocco (2003) and Campbell and Cocco (2015) find that most households should prefer an ARM, particularly younger households and households with higher rates of mobility.

In this paper, we investigate another determinant of the demand for FRMs: individuals' lifetime experience of inflation. A growing literature on experience-based belief formation in macroeconomics and finance suggests that individuals overweight their lifetime experiences relative to the optimal Bayesian scheme. Building on the notion of availability bias proposed by Tversky and Kahneman (1974), this literature posits that outcomes that occurred during one's lifetime are more easily accessible when forming beliefs and, as a result, receive extra weight compared to outcomes an individual is merely informed about or reads about. For example, in the realm of finance, Malmendier and Nagel (2011) show that stock-market experiences predict individuals' future willingness to invest in the stock market, and Kaustia and Knüpfer (2008) argue the same for IPO experiences.[2] Most related to our question, past inflation experiences strongly affect beliefs about future inflation and appear to have implications for investment in real-estate and mortgage borrowing (Malmendier and Nagel (2016), Malmendier and Steiny (2016)).

In this paper, we assess the implications of experience-based beliefs about future inflation for the contract choice of residential mortgage borrowers. We estimate their willingness to pay for the inflation protection embedded in FRMs and simulate the payoff consequences.

[1] Calculations based on Freddie Mac's Primary Mortgage Market Survey data from 1984 to 2013.

[2] Alesina and Fuchs-Schundeln (2007) relate the personal experience of living in (communist) Eastern Germany to political attitudes post-reunification. Weber et al. (1993)) and Hertwig, Barron, Weber, and Erev (2004) show how doctors' experience affect their future diagnoses.

If individuals overweight lifetime inflation experiences, their experience drives a wedge between their valuations of fixed-rate assets. Those with higher lifetime experiences of inflation will overvalue fixed-rate mortgage contracts relative to adjustable-rate alternatives since they overestimate the value of the embedded protection against future interest-rate increases. Put differently, consumers with high inflation experiences will estimate the present value of their future repayment obligations in real terms to be lower than estimated by individuals with low inflation experiences. Higher valuation implies, in turn, that such individuals are willing to pay more for a fixed-rate mortgage, relative to adjustable-rate instruments.

The experience-effect also implies that individuals with shorter lifetime histories so far overweight recent experiences more than those with longer histories. Hence, younger borrowers are predicted to respond more strongly to recent inflation experiences. Consider, for example, young borrowers coming of age during the 1970s. In the 1980s, these cohorts have recently experienced a period of high inflation, and have no personal memory of earlier periods of low inflation. The testable prediction is that mortgagors who belong to younger cohorts in the 1980s should be more likely to choose fixed-rate mortgages than older cohorts. In the 1990s, instead, then-younger mortgagors who came of age after the Volcker Fed tamed inflation should behave more like older cohorts who came of age prior to the Great Inflation.

To test the experience-effect predictions for mortgage choice, we turn to a data set that has not been explored in the context of this set of questions, 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 lender, so we have access to both demographic information and mortgage contract terms in the two cross-sections.

We estimate the structural parameters of a discrete-choice model over mortgage financing alternatives (FRM vs. ARM). Estimating this model is challenging for two reasons: first because we do not observe the contract terms of the alternative that households *did not choose*; and second, because the sample of households that choose a given product is self-selected, so suffers from selection bias. We overcome these challenges using a three-step procedure suggested by Lee (1978) and Brueckner and Follain (1988). In Step 1, we estimate a "reduced-form model" of mortgage choice, only using exogenous explanatory variables that are observable for every household. The key explanatory variables in this step are Freddie Mac

Primary Mortgage Market Survey interest rates for standardized FRM and ARM products to a representative, prime borrower in a Census region-year. In Step 2, we estimate the terms of a mortgage pricing equation where each household's FRM (ARM) interest rate depends on the FRM (ARM) survey interest rate, and on household-level characteristics associated with risk and risk preferences, including age, income, urban vs. rural location of the property, and seniority of the mortgage. These equations are likely to suffer from selection bias, since they are estimated over the nonrandom subsample of households that chose a given alternative. We use the predicted choice probabilities from the first step to control for and correct for this selection bias, using a semi-parametric control function (Newey 2009) that generalizes Heckman (1979) by including polynomial terms of the step 1 selection probability, but does not require normally-distributed errors. Identification relies on a pair of cross-equation exclusion restrictions: conditional on the FRM survey rate, the ARM survey rate does not directly influence the FRM rate that a household is offered, and vice versa. In Step 3, we use the predicted, household-characteristic adjusted pairs of mortgage rates for each household to estimate the coefficients of a structural choice model. This model is structural in the sense that the key explanatory variables are pairs of household-varying interest rates, between which each household would choose.

Our estimates of both the reduced-form and the structural mortgage-choice models indicate that individuals with higher recent inflation experiences are more likely to choose the fixed-rate alternative. Our more-conservative estimate is that between 15 and 20% of households in the population – approximately one in six households – were close enough to indifferent between the two alternatives that we can attribute their choice of an FRM to overweighting of lifetime inflation experiences. This calculation controls for the full information set available to all mortgagors in the origination year via origination-year fixed effects. The origination-year fixed effects capture the effect of current inflation as well as the entire history of all past inflation realizations (common to all market participants) at the time of origination. The choice-model estimates also provide an *ex-ante* indicator of willingness-to-pay for inflation insurance due to experienced inflation. Specifically, consumers are willing to pay between 6 and 21 basis points of interest, *ex ante*, for each additional percentage point of experienced inflation, compared to other individuals in the same origination year. This behavior is consistent with the hypothesized experience-effect model, under which borrowers overweight their lifetime inflation experiences.

Even though individuals with higher inflation experiences are more likely to choose (and more willing to pay for) an FRM, this decision could turn out to be *ex post* beneficial if inflation subsequently rises. To assess the dollar losses or gains, we simulate how much interest each individual actually paid and how much they would have paid, *ex post*, under two standardized contracts: a 30-year fully amortizing FRM, and a 30-year 1/1 ARM without caps, i.e., an ARM where the initial rate holds for one year, after which the rate adjusts annually, indexed to the one-year Treasury. We calculate the dollar cost of experience bias as the excess amount of interest paid that is attributable to the individual's experienced inflation coefficient in the structural choice equation. We estimate that, among "switching" households, the influence of personal experiences costs the typical household approximately \$8,000 (constant year 2000) over its expected tenure in the house in after-tax, present value terms, where the expected tenure is calculated based on the borrower's age. These losses are concentrated among young borrowers taking out mortgages in the mid-1980s and rise with the holding period. For example, we estimate that the present discounted value of excess mortgage interest payments for switching households taking out a mortgage in 1986 was approximately \$18,500 after-tax through 2013 (the most recent year for which we have interest rate data), assuming that the borrower held the mortgage until then. This estimate accounts for typical household refinancing behavior when FRM rates fall. Even if households refinanced optimally, the after-tax cost would still be \$17,000, and it would be as high as \$28,000 if they do not refinance at all. In all cases, the *ex-post* estimates imply the potential of significant welfare loss due to experienced inflation.

Our paper contributes to extensive research on consumer welfare in the context of residential mortgage choice. Prior to the introduction of ARMs, Kearl (1979), Baesel and Biger (1980), and Alm and Follain (1982) discussed the possibility that inflation expectations might distort housing decisions. The empirical literature on residential mortgage choice expanded significantly after regulators permitted the use of the ARM in the early 1980s, including Dhillon, Shilling, and Sirmans (1987), Brueckner and Follain (1988), and Sa-Aadu and Sirmans (1995). Follain (1990) provides an overview of this literature. Brueckner (1992) and Stanton and Wallace (1998) emphasize the importance of household mobility in the decision between fixed-rate and variable-rate mortgages. Chambers, Garriga, and Schlagenhauf (2009) solve a general-equilibrium model, focusing on the impact of payment structure on mortgage choice and homeownership rates for different types of FRMs. Finally, Koijen, Hemert, and Nieuwerburgh (2009) investigate the formation of household expectations about future mortgage rates and its implications for mortgage choice. Campbell (2013) provides an overview of the state of mortgage research and its intersections with other fields of economics. Our paper differs from previous studies in that we focus on a novel channel through which households' mortgage decisions and outcomes are influenced. We provide quantitative estimates of the direct impact of lifetime inflation experiences on the choice between FRMs and ARMs, and assess the significant welfare consequences.

Our paper builds on the growing literature pointing to the importance of experience effects. For example, Malmendier and Nagel (2011) show that people who live through different stock-market histories differ in their level of risk-taking in the stock market. They find that individuals who have experienced low stock-market returns report lower willingness to take financial risk, are less likely to participate in the stock market, invest a lower fraction of their liquid assets in stocks if they participate, and are more pessimistic about future stock returns. Malmendier and Shen (2015) show that individual experiences of macroeconomic unemployment conditions strongly affect consumption behavior — households who have experienced higher unemployment rates during their lifetime spend significantly less and are more likely to use coupons and allocate expenditure toward lower-end products. Malmendier and Nagel (2016) are able to show that experience effects work through the channel of beliefs. In the context of inflation expectations, they show that differences in lifetime experiences of inflation strongly predict differences in individuals' subjective inflation expectations. They also find that, in the Survey of Consumer Finance, outstanding mortgage balances are strongly related to lifetime experiences of inflation, but the results on type of mortgage are weak or insignificant, likely due to data limitations. Malmendier and Steiny (2016) apply the same logic to cross-country differences in mortgage borrowing across Europe. A more formal treatment of the underlying theory can be found in Malmendier, Pouzo, and Vanasco (2015), who illustrate the experience-effect mechanism in a simple overlapping-generations model with experience-based learners.

Our findings contribute to the experience-effects literature in two ways. First, we deepen the understanding of the role of experience-based inflation expectations for real-estate investment and financing decisions, providing quantitative estimates of the economic magnitude. Second, we are the first to provide structural estimates of mortgage choices and their payoff consequences under experience-based belief formation. We hope that our results provide a first stepping stone toward more complete welfare estimations.

The remainder of the paper proceeds as follows. In Section 2, we discuss the data used and provide more insitutional background. We then discuss the choice model and present our estimates of the structural choice equations in Section 3. In Section 4, we discuss how we simulate actual and counterfactual mortgage payments, and then assess the *ex post* welfare consequences of experienced inflation on mortgage choice. Section 5 concludes.

2 Data

2.1 Mortgage Choice Data

The choice of how to finance housing is a major financial decision for a typical U.S. household, with important consequences for lifetime saving and consumption patterns. The 30-year, level-payment, self-amortizing, fixed-rate mortgage with the option to prepay (FRM) has on average commanded an 80% market share in the United States over recent decades (see Figure 1, discussed below). Its popularity was encouraged by the Congress's establishment of Fannie Mae in 1938 and Freddie Mac in 1970. Their mission was to purchase long-term fixed-rate mortgages from banks which that otherwise face duration risk from holding these assets. Following the onset of the S&L crisis, the Garn-St.Germain Depository Institutions Act of 1982 allowed banks to originate adjustable-rate mortgages (ARMs). A typical ARM contract also self-amortizes over a long-term period such as 30 years, but the interest rate resets periodically according to a prespecified margin over an index, typically a one-year Treasury or a district cost-of-funds index. As a result, the monthly payments may vary from year to year. More exotic mortgage types became popular in the housing boom period of the

2000s – including "hybrid ARMs" whose interest rates are initially fixed but then become variable, and "interest-only" mortgages in which no principal is paid in early periods to keep initial payments low. Most of the analysis below will focus on the dominant contract types, FRMs and ARMs, with some comparison to mortgages with balloon payments.[3]

Figure 1 shows the time-series pattern of mortgage contract choice, and its correlation with the FRM-ARM rate spread, based on data for outstanding residential mortgages in 1991 and 2001 collected by the Census Bureau. Despite their greater liquidity on secondary mortgage markets, FRMs are priced at a premium over ARMs, in part because they provide insurance against nominal interest rate fluctuations. Freddie Mac's Primary Mortgage Market Survey reports that FRMs carried an average premium of 170 basis points over equivalent credit risk and term ARMs between 1984 and 2013, with the annual average spread fluctuating between a low of 34 basis points (in 2009) and a high of 302 basis points (in 1994) over this time period (S.D. = 67 basis points).

Our main source of individual-level data on mortgage financing and demographics is the Residential Finance Survey (RFS), which the Census Bureau formerly conducted one year after every decennial Census.[4] The unique feature of the RFS is that it consists of two cross-referenced surveys, one to households and one to their mortgage servicers. The household arm of the survey provides household demographic and income data, while the lender arm provides 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 newly-constructed residential housing. The survey oversamples multi-unit properties, particularly rental properties with 5+ units, but it is otherwise designed to be representative of the stock of outstanding mortgages in the preceding Census year.

We report some additional results using the Survey of Consumer Finances (SCF), conducted triennially by the Federal Reserve Board. The SCF has the advantage of being conducted at a higher frequency than the RFS. An important limitation of the SCF is that respondents' geographic location are not reported in the public data set due to privacy con-

[3] While this paper focuses on the choice between different available mortgages to purchase a home, Malmendier and Steiny (2016) show that macroeconomic experiences also affect the decision to buy versus rent, i.e., the extensive margin of homeownership.

[4] The RFS was discontinued prior to the 2010 Census.

cerns (with the exception of three survey waves in the 1990s). Our identification strategy relies on the inclusion of year fixed effects, so the lack of within-survey geographic variation prevents us from estimating some parameters of interest. The SCF also includes a less extensive list of mortgage contract characteristics than the RFS (for example, we only have information about refi and nonconventional status for the first mortgage on the primary residences, not for junior mortgages or for mortgages on second homes). In addition, the SCF did not ask about first-time homeowner status until 2007. On the other hand, the SCF includes a more complete picture of the overall household balance sheet, notably allowing us to control for household net worth.

For our primary analysis, we obtain microdata on the mortgages linked to owner-occupied 1-4 unit properties from the 1991 and 2001 waves of the RFS. This definition include second homes and vacation homes.[5] Since the sample is of outstanding mortgages, it has important differences from a flow dataset of mortgage originations. We do not observe any mortgages that were originated prior to the survey year and subsequently refinanced, prepaid, or defaulted upon. To approximate a flow dataset of mortgage choice situations, we restrict the sample to mortgages that were taken out no more than six years prior to the survey year (1985-1991 and 1995-2001, respectively).[6] Mortgagor age at the time of origination is a key input for calculating inflation experiences; we use the age of the self-identified primary owner if the household has multiple members. Total household income in the survey year is imputed back to the origination year by the peak-to-peak log growth rate in U.S. nominal median household income over 1980-2001 from CPS Historical Table H-6 (approximately 4.14% annually).

The RFS consistently reports data for three types of mortgage products across both survey waves: the aforementioned FRM and ARM alternatives, and balloon mortgages. This third alternative features level payments over the life of the loan that are not fully amortizing, so a large lump or "balloon" payment of the remaining principal is due at maturity, usually after 7-10 years. Balloon mortgages are designed to attract borrowers who would not otherwise qualify for a fully-amortizing product. Balloon mortgages offer lower monthly payments, and the borrower may be able to refinance upon maturity if his situation has improved, but they

[5] The public-use version of the 1991 RFS does not include a variable to let us filter these out, so we include them in all of our analysis.

[6] In the 1991 survey, origination years are only reported in intervals: 1985-86, 1987-88, and 1989-91.

carry greater risk as the borrower will have to default if he cannot refinance and cannot afford the balloon payment (MacDonald and Holloway 1996).

Borrower attributes are summarized by mortgage product choice in Table 1. Borrowers choosing ARMs tend to have higher income, are less likely to be first-time homeowners, and are more likely to be taking out a jumbo-size loan (above the conforming loan limit). There is no significant age difference between FRM and ARM borrowers, contrary to the prediction of economic theory. Moreover, lifetime inflation experiences (defined below) are actually 4.5 basis points lower for the typical FRM borrower than for the typical ARM borrower (4.76% versus 4.80%). However, this simple comparison pools across all origination years in our sample and ignores important time-series variation in the relative cost of the two products. As will be seen below (in Figure 4), individuals who have experienced higher inflation within an origination year are more likely to choose an FRM. In the main analysis, we will make this claim precise.

2.2 Inflation Experiences

We obtain the CPI-U from BLS for 1913-2013, and we use the spliced Warren and Pearson series available on Robert Shiller's website to extend this series back over 1876-1912. We then calculate experienced inflation $\pi^e_{s,t}$ in year t for individuals belonging to the cohort born in year s building on the experience effects estimated in Malmendier and Nagel (2016). Using individuals' self-reported inflation expectations in the Michigan Survey of Consumers, Malmendier and Nagel (2016) show that households' lifetime experiences of inflation significantly affect their inflation expectations. While the most recent years receive the highest weight, inflation experiences early in one's life still carry significant weight, following approximately a linearly increasing pattern (if starting from the birth year), as follows:

$$\pi^e_{s,t} \equiv \sum_{k=s}^{t} \frac{k-s}{\sum_{j=s}^{t}(j-s)} \cdot \pi_k. \tag{1}$$

π is the log change in annual average CPI-U. This formula places the highest weight on the most recent observation, and zero weight on observations prior to an individual's birth, and connects those endpoints linearly.

We illustrate the effect of this weighting formula on inflation for two representative households: an "older" household belonging to the 1945 birth-year cohort, and a "younger" household belonging to the 1960 birth-year cohort, in Figure 2. The top panel plots annual CPI-U inflation rates from 1960 to 2013 with the solid line (filled squares); the time of the "Great Inflation" is shaded in grey.[7] The lower line of hollow squares indicates a hypothetical alternative inflation path if the Great Inflation had not occurred, using a location-scale transformation of actual inflation to the non-Great Inflation mean of 2.5% and S.D. of 1.1%. In the bottom graph, we use these actual and hypothetical inflation paths to calculate the corresponding lifetime weighted-average inflation experiences, separately for the "young" and "old" cohorts. Young borrowers' beliefs are particularly affected by inflation shocks, since they have the shortest personal histories of inflation experiences. Under the hypothetical "No Great Inflation" scenario, the lifetime average of the younger cohort shoots up more, by 30 basis points, following the second oil crisis in 1979. By the late 1990s their personal inflation experiences are fairly similar. Under the actual inflation rate realizations, however, the lifetime experiences of the two cohorts diverge by significantly more, over 150 basis points, at the end of the Great Inflation. Not only does the lifetime average of the younger cohort shoot up significantly more following the inflation shocks of the 1970s; but also we see that the lifetime average remains higher for both cohorts many years later, into the 1990s and 2000s.

The important insight is that inflation shocks have a double effect, both on the level of inflation experiences and also on the cross-section. Figure 3 builds on this insight. The SCF asks respondents the following question: "Five years from now, do you think interest rates will be higher, lower, or about the same as today?" In each survey wave, we calculate the net fraction expecting interest rates to rise as the fraction answering "higher" minus the fraction answering "lower," separately for respondents above and below the sample median of 50 years old. Figure 3 plots the deviation of each group's response from the overall survey-year mean. We see that in the early SCF years (1989, 1992, etc.), members of the younger cohorts were more likely to expect interest rates to rise on net than members of the older cohorts. This relationship reverses in the mid-2000s, as younger households age and become older households; and new, younger households who put relatively less weight on the Great

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

Inflation enter the sample. The timing of this reversal in expectations concerning future interest rates coincides almost exactly with cross-sectional differences in survey respondents' lifetime inflation experiences, calculated using equation (1).

Since fixed nominal-rate contracts provide insurance against future interest rate fluctuations, we should expect that households who have higher personal experiences of inflation, and who consequently are more likely to expect interest rates to rise in the future, to be more likely to choose fixed-rate mortgages. Figure 4 shows that this is true in aggregate. We plot experienced inflation and mortgage product mix in 1985-1991 and 1995-2001 for younger versus older individuals, splitting the cohorts at the median mortgagor age of 40 in the Residential Finance Survey. This shows that younger cohorts experienced higher rates of inflation in the late 1980s, and were more likely to choose fixed-rate products than older cohorts. In the late 1990s inflation experiences between younger and older cohorts converged; at the same time, mortgage product choice also converged.

Although this is only a first, rough cut of aggregate differences in lifetime experiences and mortgage product mix, it illustrates the relationship of interest. In our main analysis, we will test whether we can detect such a pattern systematically across cohorts and over time, in a richer econometric framework. We will quantify the magnitude of lifetime experiences on individuals' mortgage financing decisions, and we will asses the economic costs of these decisions.

3 Mortgage Choice

3.1 Estimation Methodology

To test whether higher inflation experiences tilt households' choice of mortgage financing toward fixed-rate contracts, we estimate a discrete choice model over mortgage products using a three-step procedure suggested by Lee (1978) and Brueckner and Follain (1988):[8]

1. Estimate a reduced-form model of mortgage choice using exogenous explanatory variables only (equation (4) below).

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

2. Predict FRM and ARM mortgage rates at the household level, correcting for selection bias (equation (3) below).
3. Estimate a structural model of mortgage choice using individual-level predicted mortgage rates (equation (2) below).

In the first step, we estimate a reduced-form choice model where households' decisions depend on two region- and time-varying indexes of prevailing FRM and ARM interest rates. In the second step, we estimate two mortgage pricing equations, where the household's FRM (ARM) interest rate depends on the FRM (ARM) interest rate index and on household-level characteristics that adjust for risk. These equations are likely to suffer from selection bias, since they are estimated over the nonrandom subsample of households that chose a given alternative. We use the predicted choice probabilities from the first step to construct a semi-parametric control function that generalizes Heckman (1979). Identification of the semi-parametric selection-correction model comes from a cross-equation exclusion restriction: conditional on the FRM rate index, the ARM rate index does not directly influence the FRM rate that a household is offered, and vice versa. This lets us predict the menu of interest rates that each household would have been offered, correcting for any selection bias. In the third step, we estimate a structural choice model over mortgage products using the household-level menu of prices and households' lifetime inflation experiences as of the origination year.

The rest of this section describes our estimation methodology in detail. We begin by assuming that a household in choice situation n derives utility $U_{ni} = x'_{ni}\beta + \varepsilon_{ni}$ from alternative $i \in \{FRM,\ ARM,\ Balloon\}$. Alternative i is chosen if $U_{ni} > U_{nj}$ for all $j \neq i$. Utility over alternatives depends on observed components $x'_{ni}\beta$ and unobserved components ε_{ni}. Observed components may include attributes of the alternative, such as its cost, as well as attributes of the household that sway their decision toward one alternative or the other, such as liftime inflation experiences. Following McFadden (1974), we treat the unobserved utility components ε_{ni} as independently drawn from a Type I extreme value distribution. Marley (cited by Luce and Suppes 1965) and McFadden (1974) show that the implied choice probabilities can be described by a Logit formula whose likelihood function is globally concave, so the utility parameters can be easily estimated by maximum likelihood.[9]

[9] Utility is ordinal rather than cardinal, so its location and scale are not identified by the model. That is, the ratios of coefficients are identified, but the levels are not. We follow the usual practice of standardizing the

Theoretically, the mortgage payment structure preferred by a household depends on a host of demographics and proxies for risk attitudes, including age and mobility, current and expected future income, risk aversion, and beliefs about future short-term interest rates (see, among others, Stanton and Wallace 1998, Campbell and Cocco 2003, Chambers, Garriga, and Schlagenhauf 2009, and Koijen, Hemert, and Nieuwerburgh 2009). Our main observable characteristics are the alternative-specific interest rate, the borrower's income, and the borrower's age. The explanatory variable of interest is the borrower's lifetime experienced inflation. Writing this down in indirect utility terms, we obtain the following estimation equation (with the error term capturing any unobservables):

$$U_{ni} = \alpha_{it} + \beta_{Ri} Rate_{ni} + \beta_{\pi i}\pi_n^e + \beta_{Inc,i} Income_n + f_i(Age_n) + \varepsilon_{ni} \tag{2}$$

Note that we include alternative-specific year fixed effects α_{it}, which control for the overall desirability of a given alternative in a given year. The fixed effects capture all aspects of the economic environment at the time and all information that is common to all households and might enter the rational-expectations forecast, including the full history of past inflation. They are also essential for the interpretation of our coefficient of interest, $\beta_{\pi i}$. In the presence of year fixed effects, a borrower's lifetime inflation experiences should not matter, unless there is a correspondence between those experiences and borrower beliefs which differ from the baseline rational-expectations forecast. Specifically, the experience-effect hypothesis implies $\beta_{\pi,FRM} > 0$, while the standard rational framework predicts $\beta_{\pi,FRM} = 0$. (Only differences in utility affect choice probabilities, so we normalize $\beta_{\cdot,ARM} \equiv 0$ for all sociodemographic characteristics, including experienced inflation.)

The main difficulty in estimating this random utility model is that the interest rates of the non-chosen alternatives are not observed. We will solve this problem by imputing the missing data.[10] If there were no selection bias in the samples of households choosing each alternative, we could simply estimate the correlation between observed borrower characteristics and interest rates using the subsample of borrowers who chose each alternative, and then use the

variance of the extreme value distribution to $\pi^2/6$ to estimate the coefficients.

[10] Formally, imputing missing data is valid if the missing data are "missing at random," following Rubin's (1976) nomenclature. This means that the missing data distribution only depends on the unobserved data values through an observed variable: in our case, the type of mortgage each household chose.

estimated parameters to fill in the missing values for the rest of the sample. Specifically, we would estimate the parameters of the following equation:

$$Rate_{ni} = \gamma_{Ri} PMMSRate_{ni} + z_n' \gamma_i + v_{ni} \tag{3}$$

using the subset of households n choosing alternative i, and then use our estimates to predict the mortgage rate that was offered to the rest of the households, who did not choose that product. $PMMSRate_{ni}$ varies by the region and the origination year of household n. This may be viewed as the baseline price charged to a high-quality borrower. It comes from Freddie Mac's Primary Mortgage Market Survey, a weekly survey of average FRM and ARM interest rates from a representative nationwide sample of mortgage originators. The representative products are first-lien, prime, conventional, conforming mortgages with an LTV of 80% and a 30-year term. We re-weight from the five Freddie Mac regions to the four Census regions using 1990 Census housing units by state and take annual averages.[11] The other explanatory variables z_n proxy for household-specific risk characteristics, such as income, first-time home-owner status, and loan size. The error term, v_{ni}, represents unobserved factors that affect the interest rate being offered to an individual.

Of course, the subsample of individuals selecting a given alternative is probably not random. Unobserved factors influencing an individual's choice are unlikely to be symmetrically distributed around zero in the selected sample. Individuals choosing alternative i were likely offered a particularly low interest rate, so we expect the typical pricing error to be negative: $\mathbb{E}[v_{ni}|z_n, \text{chose alt. } i] < 0$. Our estimation procedure must account for this. Selection on unobserved factors poses an external validity problem when parameters estimated from the selected sample are used to impute the interest rates of the non-chosen alternatives.

An additional wrinkle is that mortgage rates are top-coded in the public use RFS files (at 14.1 percent in the 1991 survey and at 20 percent in the 2001 survey). It is well known that censoring of the dependent variable leads to inconsistency in estimators based upon conditional mean moment restrictions, including OLS. Moreover, parametric methods such as Tobit do not perform well in the presence of non-normal errors. Powell (1984) first observed that non-

[11] The RFS reports the home state of borrowers residing in a few large states. In these cases we simply use the corresponding Freddie Mac region interest rate.

parametric estimators based upon a conditional *median* moment restriction, $\mathbb{E}\left[\text{sgn}(v_{ni})|z_n\right] = 0$ rather than the usual $\mathbb{E}\left[v_{ni}|z_n\right] = 0$, are robust to censoring. We thus use a censored least absolute deviations (CLAD) estimator as our benchmark estimator of equation (3).

If we plug equation (3) into equation (2), we obtain a reduced-form choice model. Individual n, residing in Census region r in year t, derives utility from alternative i of

$$U_{ni} = \alpha_{it} + \tilde{\beta}_{Ri} PMMSRate_{ni} + \tilde{\gamma}_i{}' z_n + \beta_{\pi,i}\pi_n^e + \beta_{Inc,i} Income_n + f_i(Age_n) + \tilde{\varepsilon}_{ni} \quad (4)$$

We place tildes on coefficients and variables to emphasize that these represent different objects than in equation (2). For example, the coefficient on the PMMS rate in equation (4) is the structural coefficient from equation (2), scaled by the partial correlation between household interest rates and PMMS rates from equation (3): $\tilde{\beta}_{Ri} := \beta_{Ri} \cdot \gamma_{Ri}$. The pricing errors from equation (3), v_{ni}, are absorbed into the unobserved component of latent utility, $\tilde{\varepsilon}$: now alternative i is chosen if $\tilde{\varepsilon}_{nj} - \tilde{\varepsilon}_{ni} := (\varepsilon_{nj} + \beta_R v_{nj}) - (\varepsilon_{ni} + \beta_R v_{ni}) < (\alpha_{it} - \alpha_{jt}) + (\tilde{\beta}_{Ri} PMMSRate_{ni} - \tilde{\beta}_{Rj} PMMSRate_{nj}) + ...$ for all $j \neq i$. The important takeaway is that we have eliminated the missing data problem by replacing household-level interest rates $Rate_{ni}$ with the Freddie Mac index rates $PMMSRate_{ni}$ that do not depend on an individual household's characteristics and are always observed for both alternatives.

We now work backward, estimating equation (4) first, equation (3) second, and equation (2) third. Equation (4) may 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 reduced-form choice model probabilities to correct for selection bias in equation (3). We adopt a semi-parametric control function approach suggested by Newey (2009) in which we estimate first-stage selection probabilities, then include polynomial functions of each individual's selection probability in the second stage. This may be viewed as a generalization of Heckman (1979) to systems whose joint error distribution is non-normal. Identification requires a single-index restriction on the first-stage selection process (which a standard logit or probit model satisfies), additive separability of the selection function in the second stage, and an exclusion restriction. We assume that the Freddie Mac index rate for the nonchosen alternative doesn't directly influence the rate for the chosen alternative, except via its influence on the probability of being selected. So the ARM index is absent from the FRM pricing equation, and the FRM index is absent from the ARM pricing equation. We also exclude borrower age, age^2, and experienced inflation from the second-stage pricing equations.

Finally, we impute pairs of interest rates for each household using our selection-corrected estimates of the pricing coefficients $\gamma_i = [\gamma_{0i}, \gamma'_{-0i}]'$ in equation (3) and use these to estimate the structural choice model, equation (2). The intercept γ_{0i} is not separately identified from the control function for probability of selection. We estimate it using a method suggested by Heckman (1990), by calculating the average difference between the dependent variable and the predicted values from explanatory variables excluding the intercept, $Rate_{ni} - z'_{-0n}\hat{\gamma}_{-0i}$, over the observations whose estimated reduced-form probabilities of choosing alternative i are closest to 1.[12]

3.2 Choice Model Estimates

Table 2 presents estimates of the reduced-form multinomial logit model, equation (4), using the RFS (we present parallel results using the SCF in Appendix A). The estimation sample is borrowers aged 25-74 in the year of origination (restricted to 1985-91 and 1995-2001, respectively) for whom all covariates are available. Each coefficient represents that attribute's or sociodemographic characteristic's contribution to the utility of that alternative. So, for example, $\hat{\hat{\beta}}_R = -0.483$ in column 1, indicating that individuals derive less utility from and are less likely to choose more expensive alternatives. All columns include alternative-specific year fixed effects and control for a quadratic function of the primary owner's age. Column 1 estimates a single price coefficient on both the FRM and the ARM initial rate indices (so only the spread matters), while columns 2-4 allows the two coefficients to differ. Column 3 normalizes $\beta_{\pi,Balloon} = \beta_{\pi,ARM}$, while column 4 controls for characteristics of the mortgage (seniority, whether it is a refinancing of a previous mortgage, conventional dummy, and points paid). Finally, Column 5 omits the balloon alternative and estimates the binomial choice model between FRMs and ARMs. Recall that only differences in utility matter, so we normalize $\beta_{\cdot,ARM} \equiv 0$ for all household-level variables, including experienced inflation.

[12]The individuals in this subsample are more likely to have chosen the alternative due to observed rather than unobserved factors, so suffer from the least amount of selection bias. We use the top 10% subsample based on predicted choice probabilities for each alternative.

The results indicate that individuals who have higher levels of π^e as of the year of the choice situation derive greater utility from the FRM alternative, relative to the baseline ARM alternative. Experienced inflation reduces the utility of a balloon mortgage relative to an ARM, but this effect is imprecisely estimated and not significant at standard levels. A useful normalization is to calculate the compensating interest rate differential an individual would be willing to pay to "avoid" one additional percentage point of experienced inflation. This is done by taking the total derivative of utility for alternative i and setting it equal to zero (cf. Train (2009), ch. 3):

$$\begin{aligned} dU_{ni} = \beta_R \partial Rate_{ni} + \beta_{\pi,i} \partial \pi_n^e &= 0 \\ \left.\frac{\partial Rate_{ni}}{\partial \pi_n^e}\right|_{dU_{ni}=0} &= -\frac{\beta_{\pi,i}}{\beta_R} \end{aligned}$$

The estimates in column 1 indicate that individuals are willing to pay $0.223/0.483 = 0.462$ percentage points in the FRM - ARM spread due to an additional percentage point of π^e. Column 2 indicates that individuals are more sensitive to the fixed-rate component of the spread: individuals are willing to pay $0.220/3.56 = 0.062$ percentage points more in the FRM rate due to an additional percentage point of π^e. Since all specifications include origination year fixed effects, these effects are above and beyond the full-information inflation expectation for a given year. Fully rational individuals should place a weight of zero on their personally experienced inflation. Instead, we observe that individuals who have experienced relatively higher levels of inflation derive greater utility from the fixed-rate, inflation-insured alternative.

Figure 5 plots the fraction of households we predict would switch to an FRM if they ignored π^e. We estimate counterfactual probabilities that an individual would pick each alternative using the coefficients from Table 2, column 3, except that we force the coefficient $\beta_{\pi,FRM} = 0$, and aggregate these probabilities to calculate hypothetical product shares for each origination year. This exercise makes sense because our estimation model includes year fixed effects. The fixed effects capture all aspects of the economic environment at the time and all information that is common to all households, including the full history of past inflation. We identify the coefficient on $\beta_{\pi,FRM}$ from within-origination year variation in inflation experiences, and how these differences evolve over time. Our predicted mortgage shares add the year fixed effect coefficients back in, so adjust for the average level of inflation experiences in each origination year. In 1985-86, we predict that the FRM share would have been 32 percentage points lower (50% rather than 82%). The effect of experienced inflation diminishes as memory of the Great Inflation recedes: by 2001, the counterfactual FRM share is only 24 percentage points lower than the actual share (59% rather than 83%).

Having confirmed our hypothesis using the reduced-form model, we proceed to impute the interest rates of the non-chosen alternative and estimate the structural mortgage choice coefficients. Since the balloon alternative occupies such a small market share, we restrict the analysis to FRM and ARM alternatives from here forward. Estimates of the pricing equations (3) are presented in Table 3, without and with Newey's selection correction procedure. We use all of the exogenous explanatory variables from Table 2, except for experienced inflation and the origination year fixed effects, in the first-stage selection model.[13] Focusing on the FRM rate equations (columns 1 and 2), the main difference between the two sets of estimates is the coefficient on nonconventional status. Nonconventional mortgages carry FHA or VA insurance in order to provide eligible, higher risk households with affordable mortgages, and they tend to be FRMs rather than ARMs. Before we correct for sample selection, the coefficient on the nonconventional mortgage dummy is a positive number, +6 basis points (column 1); after correcting for selection, it is -35 basis points (column 2). This is consistent with high-risk households selecting into nonconventional, FRM mortgages, and the median pricing error, conditional on choosing an FRM, being less than zero.

We find evidence of less selection bias in the ARM initial rate pricing equations (columns 3 and 4). CLAD is not particularly useful for adjusting ARM margins for household risk characteristics, as more than half of all individuals carry the same margin (2.75 percentage points). Whether or not we control for selection, conditional-median based methods only adjust the margin for mortgage seniority (junior mortgages are 25 basis points more expensive than first mortgages). In later sections of the paper, we discretize the distribution of margins into ten intervals (using the 1991 RFS reporting intervals) and estimate an ordered logit model of ARM margin on the same set of covariates shown in Table 3. This model also accounts for

[13]We omit these variables so that our structural estimates do not build the role of inflation experiences into the model and "assume the conclusion."

censoring and allows us to recover coefficients to predict risk-adjusted ARM margins. The estimation results are not shown but are available upon request.

Table 4 presents estimates of the structural choice equation (2). The dependent variable is coded as 1 if the household chose an FRM and 0 if it chose an ARM. We use predicted interest rates from the pricing equations presented in Table 3 for both the chosen and the nonchosen alternative in each choice situation. Standard errors are not adjusted for the first-stage estimation. A comparison of columns 1 and 2 indicates the importance of the selection-correction in equation (3). Without selection correction, the price coefficients are the wrong signs, indicating upward sloping demand curves. After we switch to the selection-correction estimates, the signs become correct (column 2).

The structural model estimates confirm our previous finding that experienced inflation influences mortgage contract choice, above and beyond the information set available to all households in a given origination year. Individuals exhibit an *ex ante* willingness to pay of $0.223/1.065 = 0.209$, i.e., 21 additional basis points of FRM interest for every additional percentage point of experienced inflation (based on the estimates from column 2). A comparable calculation to Figure 5 suggests that the FRM share would fall by 15-20 percentage points if individuals ignored their lifetime inflation experiences and behaved like everyone else in the same origination year. As before, the effect is concentrated in the late 1980s and diminishes in the late 1990s.

Columns 3 and 4 present estimates of the structural model using risk-adjusted ARM margins. As before, the signs on the FRM rate and ARM initial rate are the wrong sign without the selection correction. With the selection correction, these signs reverse and are correct; however, the sign on the ARM margin remains negative (indicating that a higher margin is associated with a lower probability of choosing an FRM). Since the selection correction procedure mainly affected the coefficient on the nonconventional status dummy in the pricing equations in Table 3, we hypothesize that nonconventional status might have an additional effect on mortgage choice above and beyond its structural impact on mortgage prices. To confirm this, we re-run the last two sets of estimates with nonconventional status as an additional explanatory variable in Table 4, columns 5 and 6. Inclusion of this variable generates "correct," negative demand elasticities in both specifications.

The bottom line is that in all specifications, higher levels of lifetime inflation experiences are associated with a greater probability of choosing an FRM compared to other individuals in the same origination year, independently of how we estimate mortgage prices and of what variables are controlled for. This is consistent with personal experiences affecting an individual's *ex ante* willingness to pay for the safety of the fixed-rate alternative. But does this translate into an *ex post* welfare loss?

3.3 Inflation Experiences and Dollar Holdings

Individuals with higher inflation experiences are more likely to ignore price signals and choose a fixed-rate mortgage. In this section, we show that they also tend to originate and hold larger dollar balances of fixed-rate liabilities.

We follow the methodology laid out in Malmendier and Nagel (2016), who explore this question using the SCF. For each birth-year cohort in the RFS, we calculate the average, per-capita dollar amount of fixed- and adjustable-rate mortgage holdings per year. We then estimate the following equation:

$$log(\overline{Balance}_{ct}) = \alpha_t + \alpha_{\text{age}} + \beta_\pi \pi^e_{ct} + \gamma log(\overline{HHInc}_{ct}) + u_{ct} \tag{5}$$

where c indexes a birth-year cohort and t is the year of observation. Since we observe each cohort in multiple years, we may separately control for year and age fixed effects. Unlike Malmendier and Nagel (2016), we do not observe any data on household wealth.

Table 5 shows the estimation results. Columns 1-4 of the table calculate per-capita mortgage balances as of the RFS survey year ($t = 1991$ or 2001), among all homeowners between the ages of 25 and 74 surveyed in the RFS, including those individuals who have zero mortgage balances. We provide separate estimates for the remaining balance of all mortgages (columns 1-2) and the remaining balances of mortgages originated recently, in the last two years (columns 3-4). Columns 5-6 calculate per-capita mortgage originations among members of the cohort who originated a mortgage during the six years prior to the survey ($t \in \{$1985-91, 1995-2001$\}$).

All six columns tell a similar story. Cohorts with higher inflation experiences tend to both hold higher average amounts of fixed-rate mortgage balances in the survey year, and to originate larger fixed-rate loans in the years prior to the survey year. However, we find no correlation between inflation experiences and ARM balances or loan amounts, conditional upon the other control variables in equation (5). These results are reassuringly similar to the results reported in Malmendier and Nagel (2016), despite coming from a different survey covering different years and sampling from a different population (homeowners rather than consumers).

4 Simulations

4.1 The Welfare-Relevant Treatment Effect

While the effect of experienced inflation on mortgage product shares appears to be economically large, it is not obvious that this is a costly mistake. Figure 6 plots the path of the national PMMS fixed-rate and adjustable initial rate indices, and the yield on a one-year constant maturity Treasury plus a standard margin of 2.75 percentage points, between the years 1986 and 2013. The FRM-ARM initial rate spread is always positive but varies over time (as previously seen in Figure 1, this variation is correlated with product shares). Individuals with a sufficiently short time horizon will usually benefit from the initially low rate of an ARM, but over longer time 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% for the life of the loan. An individual taking out a 1/1 ARM with no caps on rate resets would pay the much lower initial rate of 4.58% in 1993, but this would reset to 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.

To assess *ex post* welfare consequences of experienced inflation, we need (first) to identify the subset of the population that is affected and (second) to calculate whether this mistake was costly or beneficial. First, some households would have chosen the same mortgage product regardless of whether they overweighted or ignored experienced inflation. The relevant subset of the population are the "switchers." These households were just on the margin between an ARM and an FRM; they chose an FRM *because* experienced inflation figured into their choice function above the optimal weight it should receive in a full-information, Bayesian forecast of future nominal interest rate movements. Second, as shown in Figure 6, there are periods when timing the market and locking in a low nominal fixed-rate debt contract would be advantageous. So even if households are making a mistake, it could turn out to be *ex post* beneficial.

Using our estimates of the mortgage pricing equations in Table 3, we can simulate the actual and counterfactual monthly payments each household would make under both an FRM and an ARM. We assume that all mortgages are originated on January 1, carry a 30-year term, are self-amortizing, and are paid on time (no late penalties or prepayments). We consider three different interest rate scenarios. In Scenario 1, we do not predict individual interest rates, but rather assign everyone the Freddie Mac PMMS index mortgage rate, varying only by region where they live. This sidesteps the issue of estimating individual-level pricing equations but may overstate the magnitude of welfare losses by not correcting mortgage rates for household risk characteristics. In Scenario 2, we use selection-corrected CLAD to predict risk-adjusted FRM rates and ARM teaser rates, while ARM margins are only adjusted for seniority (corresponding to Table 3 columns 2, 4, and 6). In Scenario 3, we use ordered logit to predict individual-varying ARM margins based upon household-level characteristics. Individuals choosing an ARM receive the teaser rate for one year, after which annual resets are based the appropriate margin over the average value of a 1-year constant maturity Treasury for that year: plus 2.75 percentage points (Scenario 1), plus 2.75 if first-lien and 3.00 if second- or third-lien (Scenario 2), or plus a risk-adjusted margin from the selection-corrected ordered logit estimation results (Scenario 3). The scenarios are summarized below:

Scenario:	**1**	**2**	**3**
FRM Rate	Freddie Mac PMMS	Risk-adj. (CLAD)	Risk-adj. (CLAD)
ARM Initial Rate	Freddie Mac PMMS	Risk-adj. (CLAD)	Risk-adj. (CLAD)
ARM Margin	1-year T-bill + 2.75	Seniority-adj. (CLAD)	Risk-adj. (OLOGIT)

Each scenario has limitations. Scenario 1 makes no adjustment for mortgagor risk characteristics, but it also carries the least amount of sensitivity to researcher uncertainty about the true pricing model. Scenarios 2 and 3 make progressively greater adjustments for risk characteristics, at the cost of increasing sensitivity to our modeling assumptions. However, take note that our simulated ARM contract has no caps on annual or lifetime interest rate adjustments. Since many ARMs are capped, all three scenarios overstate the amount of interest rate risk in an ARM and underestimate the potential savings from choosing an ARM over an FRM. This biases against our maintained hypothesis that experienced inflation is welfare-reducing.

The welfare cost for switching households is easily described using the language of potential treatments and potential outcomes. For ease of exposition, we focus on the binary choice problem and number the FRM alternative as 1 (and the ARM alternative as 0). In every choice situation n, the household faces two potential outcomes: mortgage payments under the fixed-rate alternative, $Y_{n,1}$, and mortgage payments under the adjustable-rate alternative, $Y_{n,0}$. The observed set of mortgage payments in our data is

$$Y_n = D_n Y_{n,1} + (1 - D_n) Y_{n,0}$$

and depends on an individual's mortgage choice ("treatment status"), $D_n \in \{0, 1\}$, indicating which alternative is chosen. The value of D_n depends on the difference in latent utility between the two alternatives from equation (2):

$$\begin{aligned} D_n &= \mathbb{I}\{\text{FRM is chosen in choice situation } n\} = \mathbb{I}\{U_{n,1} > U_{n,0}\} \\ &= \mathbb{I}\{-(\varepsilon_{n1} - \varepsilon_{n0}) < x'_{n1}\beta_1 - x'_{n0}\beta_0\} \end{aligned}$$

The FRM is chosen if the difference in observed components of latent utility exceed the difference in unobserved components. Observed latent utility may include alternative characteristics, such as prices, and household characteristics, including experienced inflation. These are the coefficients estimated in Table 4.[14]

Under a counterfactual utility model, the same individual in the same choice situation might make a different choice. This introduces the notion of potential choices ("potential treatments"). Specifically, let $D_n(b_\pi)$ be the choice individual n would make given experienced

[14] Since only differences in utility matter, we are implicitly estimating the difference in household characteristic coefficients in the binary choice model: $\beta_{x,1} - \beta_{x,0}$.

inflation coefficient b_π. The observed mortgage choice in our data is

$$D_n = \int A_n(\beta_\pi) D_n(b_\pi) db_\pi$$

where $A_n(\cdot) = \mathbb{I}\{b_\pi = \cdot\}$ and β_π is the true experienced inflation coefficient, representing the additional weight placed on π^e beyond the full-information Bayesian optimum. The household's actual choice, under the true utility model, is $D_n(\beta_\pi) \in \{0, 1\}$. The welfare-relevant counterfactual is the choice the household would have made in the same choice situation if placing no additional weight on experienced inflation: $D_n(0) \in \{0, 1\}$. If $D_n(\beta_\pi) = D_n(0)$, then "assignment" was irrelevant and experienced inflation did not influence the household's mortgage choice. If $D_n(\beta_\pi) \neq D_n(0)$ – the two potential choices are different – then the household is nearly indifferent and would switch under the counterfactual model.

Using this notation, the *ex post* welfare loss (or gain) for switching households may be expressed as follows:

$$\mathbb{E}[Y_{n,1} - Y_{n,0} | D_n(\beta_\pi) = 1, D_n(0) = 0] \tag{6}$$

By monotonicity of the choice function $D_n(\cdot)$ and $\beta_\pi > 0$, households only switch out of an FRM. So the average welfare loss is the expected difference between FRM and ARM payments for those households that chose a fixed-rate mortgage because of the weight they placed on their personal inflation experiences. Positive numbers represent overpayment, a welfare loss, and negative numbers represent underpayment, a welfare gain. The conditioning set restricts us to the subset of households in the population for whom experienced inflation was the determining factor in their mortgage choice.

The inference problem is threefold. First, we do not know β_π; second, we observe the actual choice $D_n = D_n(\beta_\pi)$ but not the counterfactual choice $D_n(0)$; and third, we only observe one of the two potential outcomes $(Y_{n,0}, Y_{n,1})$ for each choice situation. However, by Bayes' rule:

$$\begin{aligned} \mathbb{E}[\Delta Y_n | D_n(\beta_\pi) = 1, D_n(0) = 0] &= \int \Delta y \cdot f(\Delta y | D_n(\beta_\pi) = 1, D_n(0) = 0) d\Delta y \\ &= \frac{\int \Delta y \cdot h(D_n(\beta_\pi) = 1, D_n(0) = 0 | \Delta y) f(\Delta y) d\Delta y}{g(D_n(\beta_\pi) = 1, D_n(0) = 0)} \end{aligned} \tag{7}$$

We have all of the pieces in hand to estimate equation (7). We have already described our three scenarios for simulating the FRM and ARM mortgage payments $(Y_{n,0}, Y_{n,1})$ above, relying upon the estimates in Table 3. The probability mass function $h(\cdot|\Delta y)$ gives the probability that a household is nearly indifferent between the FRM and ARM choices and would switch to an ARM were it not for the presence of recent inflation experiences in its choice function. The probability that the household is a switcher is the difference between the true FRM choice probability and a counterfactual FRM choice probability:

$$h(D_n(\beta_\pi) = 1, D_n(0) = 0|\Delta y) = P(D_n = 1|b_\pi = \beta_\pi, \Delta y) - P(D_n = 1|b_\pi = 0, \Delta y)$$

For example, if a household's true probability of choosing an FRM is 90% and the counterfactual probability (ignoring its experienced inflation) is 70%, then for every 100 observationally-equivalent households in the population, we would expect 70 of them to choose an FRM no matter what, 10 to choose an ARM no matter what, and 20 to switch from the FRM to the ARM. These choice probabilities may be obtained by calculating predicted values from the choice equation estimates in Table 4.

To summarize, we estimate the Welfare-Relevant Treatment Effect as a weighted average of the difference in mortgage payments:

$$\begin{aligned} \hat{\mathbb{E}}[Y_{n,1} - Y_{n,0} \quad & | \quad D_n(\beta_\pi) = 1, D_n(0) = 0] \\ & \propto \quad \frac{1}{N}\sum_{n=1}^{N} \Delta\hat{y}_n \cdot [\hat{P}(D_n(\hat{\beta}_\pi) = 1|\Delta\hat{y}_n) - \hat{P}(D_n(0) = 1|\Delta\hat{y}_n)] \end{aligned} \tag{8}$$

where the weights are proportional to the difference in probability of choosing an FRM under the estimated ("true") and counterfactual experienced inflation coefficients. This differs from standard objects reported in the treatment literature. For example, an Average Treatment Effect might be defined as

$$\mathbb{E}[Y_n|b_n = \beta_n] - \mathbb{E}[Y_n|b_n = 0] = \sum_{i=0}^{1} P(D_n(\beta_\pi) = i) \cdot Y_{n,i} - \sum_{i=0}^{1} P(D_n(0) = i) \cdot Y_{n,i}$$

The ATE would be estimated as an unweighted average of the difference in expected payments, using the actual versus the counterfactual choice probabilities.[15]

Figure 7 illustrates these calculations by presenting our estimates of the two potential outcomes – *ex post* mortgage payments under a fixed-rate contract versus an adjustable-rate contract – for two particular origination years, 1986 and 1996, between the origination year and the survey year. Potential payments are calculated based on Scenario 1 – using the Freddie Mac PMMS interest rates and a 2.75 percentage point margin over Treasury – so the only variation across households is by region and origination amount. All calculations were performed after converting the loan amounts into constant 2000 dollars.

Each pair of bars represents the two hypothetical, counterfactual outcomes for the same set of households: annual mortgage payments from choosing a fixed-rate mortgage (left bar) or an adjustable-rate mortgage (right bar). Due to the self-amortizing feature, the majority of the early payments goes towards interest (the solid area) rather than principal (the shaded area). The total FRM payment is of course fixed, while the total ARM payment varies from year to year because of resets.[16] The average mortgage originator in 1986 would have done better by choosing an ARM in every year between 1986 and 1991, given the *ex post* path of Treasury rates. An important advantage of the ARM is that by carrying a low initial rate, the holder makes larger payments towards principal in the early years of the mortgage. This keeps future payments lower than they would otherwise be: for example, in 1989 (year 3 in the left panel of the graph), resets pushed the ARM rate up to 11.3%, above the counterfactual FRM rate of 10.19%; but the total ARM payments remained below total FRM payments because the remaining balance on the typical ARM would have been lower. In contrast to 1986, ARM rates increased quickly after 1996, pushing average ARM payments at or above average FRM payments under the two hypothetical scenarios.

4.2 Refinancing Behavior

A fixed-rate mortgage without the option to prepay is a very risky contract, since the *ex post* real rate could rise dramatically if actual inflation is less than expected inflation. Most

[15]Heckman and Vytlacil (2007) define an object called the "policy-relevant treatment effect," using the same weighted average that we derive above.

[16]Even though the origination amounts are deflated, the loan payments are still in nominal terms since we are using nominal interest rates. Inflation would erode the real value of future payments, producing a downard tilt in the FRM graph.

mortgages in the U.S. allow the borrower to refinance without paying a penalty. To accurately gauge the *ex post* welfare cost of holding a fixed-rate versus an adjustable-rate mortgage, we need to consider households' likely refinancing behavior.

We consider three sets of assumptions about refinancing. First, we estimate the present value of mortgage payments assuming that the household holds the original fixed-rate mortgage until maturity, as would happen if the contract prohibited prepayment. This is a worst-case scenario for an FRM in a dis-inflationary environment, and provides an upper bound to our welfare estimates. Alternatively, we assume that the household refinances whenever the difference between the new interest rate and the old interest rate falls below a threshold that accounts for the fixed cost of refinancing and the option value of waiting. A closed-form solution for this threshold was recently provided by Agarwal, Driscoll, and Laibson (2013, hereafter referred to as ADL). We use their square-root rule approximation to the optimal threshold:

$$OT_{n,t} \approx -\sqrt{\frac{\sigma\kappa}{M_{n,t}(1-\tau)}}\sqrt{2(\rho+\lambda_{n,t})} \tag{9}$$

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 parameterize $\sigma = 0.0109$, $\kappa = \$2000$, $\tau = 0.25$, and $\rho = 0.05$. ADL allow for three sources of exogenous mortgage prepayment:

$$\lambda_{n,t} = \mu + \frac{Rate_{n,FRM}}{\exp(Rate_{n,FRM}(T-t)) - 1} + \pi$$

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 mortgage with $T - t$ years remaining due to self-amortization.[17] The third term represents declines in the real value of future mortgage payments due to inflation. This could be allowed to vary over time with actual inflation, but for simplicity we set $\pi = 0.04$.

Optimal refinancing behavior is a best-case scenario for mortgagors with a fixed-rate mort-

[17] See ADL Appendix D for a derivation of this expression.

gage. An extensive literature documents that mortgagors do not exercise this real option optimally (Green and Shoven 1986, Stanton 1995, Green and LaCour-Little 1999, Bennett, Peach, and Peristiani 2000, Agarwal, Rosen, and Yao 2015, Andersen, Campbell, Nielsen, and Ramadorai 2015, Bajo and Barbi 2015, and Keys, Pope, and Pope 2016, among others). Households sometimes refinance too early, before the rate differential has crossed the threshold, or too late, waiting months or years after the differential has crossed the threshold before refinancing. Agarwal, Rosen, and Yao (2015) refer to these as "errors of commission" and "errors of omission," respectively. To estimate a household's expected fixed-rate mortgage payments, we estimate the set of probabilities that household n is holding a year-s mortgage in year $t \geq s$, i.e., that the household last refinanced in year s. This provides an intermediate case between the two extremes of no refinancing and optimal refinancing.

Specifically, we borrow estimates from Andersen, Campbell, Nielsen, and Ramadorai (2015) describing the probability that a household will refinance in a given month as a function of the "incentive to refinance" – the difference between the optimal threshold and the actual rate differential. Their baseline estimates are

$$P(Refi_{n,t,m}|y_0) = \Phi\left(-1.921 + \exp(-1.033) \times (OT_{n,t} - (y_{n,t} - y_0))\right) \tag{10}$$

where y_0 is the interest rate on the outstanding fixed-rate mortgage and $y_{n,t}$ is the interest rate on a new mortgage issued after refinancing in year t.[18] We convert from a monthly to an annual time horizon by assuming that monthly refinancing events are i.i.d. within a year: $P(Refi_{n,t}|y_0) = 1 - (1 - P(Refi_{n,t,m}|y_0))^{12}$. These refinancing probabilities correspond to transition probabilities between the "state" of holding a year s mortgage and a year t mortgage:

$$r_{n,t,s} \equiv P_n(S_t = t|S_{t-1} = s) := P(Refi_{n,t}|y_0 = y_{n,s}) \cdot \mathbb{I}\{s < t\}$$

Beginning with the initial condition that $P_n(S_1 = 1) = 1$, we iteratively solve for the unconditional probabilities $P_n(S_t = s)$ describing the probability that household n will hold a mortgage last refinanced at time s in year t.[19]

[18] From Andersen, Campbell, Nielsen, and Ramadorai (2015) Table 9, column 1. Their sample is of Danish households over the years 2008 to 2012.

[19] A final issue with this is keeping track of the household's outstanding mortgage balance at the beginning

These calculations are illustrated for a sample household in Table 6. The column labeled "Potential FRM Rates" gives the rate that we estimate this household would receive if it refinanced into a new FRM that year based on Scenario 3. The next column provides the "Optimal Threshold" for refinancing given the household's current outstanding mortgage balance and time remaining to maturity according to equation (9). At the beginning of year 4, mortgage rates had fallen by 109 basis points since year 1 (9.29 - 10.38). This exceeds the optimal refinancing threshold of 95 basis points, so the household should refinance. However, we estimate that there is only a 30% chance that the household will do so: $P_n(S_4 = 4) = 0.30$. This reflects both types of refinancing errors discussed earlier–the household might have already refinanced in year 2 or 3, or the household might ignore the incentive and wait an extra year. Figure 8 shows the path of FRM rates for this household under the three cases graphically. "Expected" rates mostly track "optimal" rates with a lag, indicating the importance of errors of omission in expected refinancing behavior.

Table 7 illustrates the interest component of mortgage payments for the same household under the three sets of assumptions about refinancing behavior. Under the "Expected Refinancing" scenario, the present value of interest payments over from 1988 to 2012 is $176 thousand using an 8% nominal discount rate. Assuming that the household faces a marginal tax rate of 25%, the present value of its interest deductions are $44 thousand. The present value of refinancing costs (which are not tax deductible) is $4,705, generating a bottom-line cost of $137 thousand.

As expected, the present value of FRM payments is highest if the household never refinances and lowest if the household refinances optimally. Taking out an ARM would have been cheaper than an FRM over this time horizon, regardless of refinancing behavior. Under optimal behavior, the FRM is just ovver $6 thousand more expensive. This figure rises to $11 thousand if the household refinances as expected, and could be as high as $35 thousand if the household never refinances.

of each year. This state variable is non-Markov and 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.

4.3 Simulation Results

4.3.1 Scenario 1

We run the simulation using Scenario 1 interest rates to obtain a pair of potential outcomes $(Y_{n,0}, Y_{n,1})$ for all households in our dataset. Weighting by the change in probability of choosing an FRM under the true latent utility model (Table 2, column 3) and the counterfactual ($\hat{\beta}_\pi = 0$), we calculate the WRTE as described in equation (8). Summaries by mortgage origination year are presented in Figure 9, assuming no refinancing.

This figure shows the accumulated excess interest for all switching households, with no discounting or reinvestment, indicating how costly it has been for each set of borrowers to hold on to their mortgage and not refinance. *Ex post* welfare losses are much higher for mortgages originated in the 1980s, both because the disparity in experienced inflation across cohorts is much higher and because fixed-rate mortgages were relatively expensive during this time period (Figures 1 and 2). On average, borrowers in the 1991 RFS had cumulatively paid \$4,300 in extra interest due to experienced inflation (as of year-end 1991), and borrowers in the 2001 RFS had cumulatively paid \$1,500 extra (as of year-end 2001). Losses are particularly large for borrowers in 1986. For all but one origination year, overweighting experienced inflation is *ex post* costly. The exception is 1998, when FRM rates were unusually low. For these borrowers, overweighting experienced inflation and taking out an FRM turned out to be *ex post* advantageous.

4.3.2 Scenarios 2 and 3

Scenario 1 assigns each borrower the average mortgage rate according to the Freddie Mac survey of mortgage originators. Since average ARM rates and margins declined through much of the 1980s and 1990s, it would have been *ex post* costly for a borrower to take out and hold an FRM at the average interest rate. Of course, it is likely that choice-situation specific price differentials also played a role – individuals taking out an FRM or ARM were likely offered more advantageous than average interest rates on their chose alternative. In Scenarios 2 and 3 we use the selection-corrected mortgage pricing equations from Table 3 and the choice probabilities obtained from the structural choice model in Table 4, to simulate potential mortgage payments and welfare effects.

Table 8 presents the *ex post* welfare loss (gain) for switching households, comparing the after-tax present discounted value of mortgage payments with counterfactual payments conditional on the household not placing extra weight on experienced inflation. The middle panel presents results for Scenario 2. Interest rates are predicted from equation (3), estimated by selection-corrected CLAD in Table 3 columns 2 and 4. ARM margins are set to 2.75 percentage points over the one-year Treasury rate for first-lien (senior) mortgages, and 3.00 percentage points over Treasury for second- and third-lien mortgages.

As of the RFS sample year, we estimate that the average switching household had overpaid by $2,668 (the "No Refi" row). This estimate is likely biased toward zero. Since the RFS is a survey of outstanding mortgages, we are missing the original interest rates and refinancing costs for mortgages that were originated and refinanced in the six years prior to 1991 or 2001.[20] These unobserved households are likely among the biggest overpayers who had the most to gain by refinancing, so including them would only increase our estimate of the true average cost.

Reading across the "No Refi" row, we see how costly continuing to hold the mortgage would be if *none* of our switching households refinanced by projecting beyond the survey year and up to the present. The WRTE doubles at a time horizon of five years, to $6,000 per household. After 20 years, the WRTE exceeds $22,000 per household in after-tax present value terms. This represents an upper bound on the potential average welfare loss. Allowing households to refinance somewhat ameliorates this cost. However, even under the "Optimal Refi" scenario, the WRTE is nearly $10,000 per household on average. This underscores that for most switching households, taking out an FRM was likely a very costly mistake *ex post.*

The bottom panel of Table 8 repeats the exercise for scenario 3. Based on risk-adjusted margins, we estimate that 16.4% of households in the two survey years would not have chosen an FRM, except for the undue influence of experienced inflation. In the survey year, the average WRTE is approximately $2,383 per household in after-tax present-value terms, and after 20 years, the average welfare loss again exceeds $22,000 per household. As before, the present discounted WRTE is smaller but still positive if the households are allowed to

[20] We are also missing any mortgages that were defaulted upon or prepaid in full.

refinance, between \$9 and \$11 thousand in constant year-2000 after-tax dollars.

To generate a bottom-line number for each of these three scenarios, we estimate each household's probability of moving each year as a function of the householder's age. We obtain 5-year non-mover rates from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) for 2000-05 and 2005-10 for the general U.S. population at least 20 years old by 5-year intervals, which we code to the midpoints.[21] We convert the survival rates into one-year moving probabilities and fit them to a fourth-order polynomial function of householder age. This generates a downward sloping curve of each householder's moving probability. For example, we estimate that a 25-year old householder has a 17.4% probability of moving. This declines to 13.1% by age 30 and 5.1% by age 50.

We assume that moving events are exogenous and unanticipated by the household, arriving according to the empirical distribution we have just estimated. Upon moving, the household sells the house and the stream of mortgage payments stops. Using these probabilities, we re-calculate the present discounted value of the mortgage interest payments, weighting each payment by the probability that the household has not yet moved. These results are reported in the final column of Table 8, labeled "E[tenure | age]". The order of magnitude roughly resembles our estimtes for a 10-year holding period (although we are now putting some positive probability on the entire holding period through the end of our data in 2013). According to scenario 3, we estimate a baseline cost of \$8,391 per switching household, incorporating both expected refinancing behavior and the probability of moving.

4.3.3 Geographic Mobility and Expected Tenure

Our baseline methodology to estimate expected tenure in the house is completely nonparametric and relies only on the borrower's age. However, a literature dating back to Dunn and Spatt (1988) suggests that lenders use a menu of discount point-interest rate combinations to incentivize borrowers to self-select based on private information about their mobility.[22] Discount points represent a trade-off between an upfront cost and a future benefit. Each discount point costs 1% of the amount borrowed, and buys approximately a 25 basis point

[21] The data include both renters and homeowners.

[22] However, see Agarwal, Ben-David, and Yao (2017) for recent evidence that borrowers do not pay points optimally.

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 using National Association of Realtors data for the early 1990s. In our data, 16.5 percent of households pay discount points, with a median of 2 points paid.

Common investment advice on popular household finance websites suggests that borrowers should pay points if their expected tenure in the house exceeds the break-even horizon when the lower monthly payments just offset the upfront cost.[23] In theory, a risk-neutral household should keep paying points until its expected tenure in the house exactly equals the break-even time it will take to recover the upfront payment. In practice, households might pay fewer than the optimal amount of ponts due to liquidity constraints at the time of mortgage origination or risk aversion.

With a few assumptions, we can use this information to construct a distribution of moving probabilities for each household. First, we assume that the point-rate schedule is quadratic as described above. We then calculate the break-even horizon τ^* for each household in our dataset, assuming that the monthly interest savings are discounted at an annual nominal rate of 8%. If we also assume that the moving events arrive following a Poisson process, then the distribution of moving times τ is negative exponential with intensity parameter $\lambda = 1/E[\tau] = 1/\tau^*$. This distribution implies that the hazard rate of moving is stationary. Alternately, if individuals form an attachment to their communities over time, as suggested by Dynarski (1985) and Quigley (1987), then the hazard rate of moving might decrease with time. To model this, we also let moving times follow a Weibull distribution with shape parameter $\alpha = 0.7$.[24] "Survival" curves for one of the households in our sample are plotted in Figure 10. This household paid 3 discount points, implying a break-even horizon of $\tau^* = 6.9$ years.

Table 9 reports expected additional interest payments made by switching households, over different distributions of moving times. The first column replicates the last column of Table 8 for reference. The present discounted values are somewhat lower using the points

[23] See investopedia.com/articles/pf/06/payingforpoints.asp and bankrate.com/finance/mortgages/mortgage-points.aspx.

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

paid methodologies; for example, column (2) reports a WRTE of \$5,275 under Scenario 3 interest rates, expected refinancing behavior, and Poisson moving events, roughly \$3000 less than our age-based estimate. Ths is in part due to the large discrepancy in occupancy times: the average median tenure is 4.7 years across switching households based on discount points paid, versus 12 years based on householder age. This is because most households do not pay discount points. If households pay less than the optimal number of points for one of the reasons discussed above, then our estimates of occupancy time are too short – expected tenure will exceed the break-even horizon. We model this by fitting each household's intensity parameter to the median rather than the mean of the distribution: $F_{\lambda}^{-1}(\tau^{*}) = 0.5$. This raises the average median time of occupancy to 6.6 years, and reduces the gap between the dollar costs estimtaed under the two methodologies. For example, column (5) reports a WRTE of \$6,700 under Scenario 3, expected refinancing behavior, and a decreasing hazard rate of moving, approximately \$1,700 less than our estimate when modeling mobility from age.

In principle we could use other methodologies to back out households' moving probabilities (such as comparing the distributions of outstanding mortgages in the 1991 versus the 2001 surveys). However, the evidence presented in this section suggests our baseline results are robust to a wide array of assumptions.

4.4 Different Inflation Environments

An important limitation to our *ex post* estimates is that they rely on the actual realization of historical inflation subsequent to each mortgagor's origination date. This ignores the range of other possible inflation environments that might have occurred, and thus misses the utility value of the inflation insurance implicitly embedded in a fixed-rate mortgage. To consider the value of this inflation insurance, we re-simulate interest payments for switching households under other inflation environments.

4.4.1 Historical Environments of Rising versus Falling Inflation

The expected path of future inflation will affect the slope of the nominal yield curve, and thus the FRM-ARM spread, today. Rather than assuming a particular model for the term structure, we first use historical inflation and term structure data to engage in a thought experiment: what would be the WRTE for the households in our sample if they had originated their mortgages under a different historical inflation environment? We choose two points in time that represent a rising versus a falling inflation environment: 1971, just before the Great Inflation took off, and 1981, the year that inflation began to subside and FRM rates peaked. We assume that the households are completely identical in every respect, including their lifetime inflation experiences, except that they are facing the FRM - ARM interest rate schedule of 1971 or 1981 instead of their actual origination year.

We use Scenario 3 estimates to predict risk-adjusted FRM and ARM interest rates for each household starting from these two origination years. Since ARMs were introduced in the U.S. in 1982, we have to impute a baseline ARM price for 1971 and 1981. We assume that the Freddie Mac ARM index would have taken its average value over the 1-year constant-maturity Treasury rate – 1.5 percentage points – had ARMs existed and the data been collected. To calculate the WRTE, we use the same actual and counterfactual choice probabilities we previously estimated, which depend on both the actual origination year interest rate schedule and on an origination year fixed effect. That is, we do not allow for differences in initial prices or the starting year to affect the probability that a household would switch when we turn the inflation experience coefficient off. Finally, we estimate the distribution of moving times nonparametrically using householder age.

The results are reported in Table 10. In a rising inflation environment the WRTE is negative, indicating that households who choose an FRM instead of an ARM due to their inflation experiences end up paying less. The average switching household is better off by between $13 and $14 thousand dollars. This represents a best-case scenario for choosing an FRM: due to rising inflation over the 1970s, it is never optimal for any of the households in our sample to refinance for the first twenty years of the mortgage's life (so the "No Refi" and the "Optimal Refi" values are very close to each other). The dollar benefit of choosing an FRM under this inflation history is 1.5 to 2 times the magnitude of the dollar cost we estimate given actual inflation behavior.

In a falling inflation environment such as 1981, choosing an FRM is costly even if a household refinances close to optimally. We estimate that the average switching household would pay approximately $10,300 more over its expected lifetime in the house, given expected refinancing behavior. This is about 20% larger than our baseline estimate given actual inflation behavior.

This exercise suggests that there is utility value to the inflation insurance of an FRM contract, even though this insurance was rarely in the money during the Great Moderation of the 1990s and 2000s. It is worth asking whether the cost we estimate is a reasonable price to pay for households wishing to reduce their exposure to inflation risk.

4.4.2 Simulated Inflation Environments

To consider a wider range of possibilities, we simulate 100 different inflation environments.

In each simulation, we draw 30 years of inflation and nominal mortgage rates. We then use the risk-adjustments from Scenario 3 to predict the counterfactual FRM and ARM rates that each household would face over the lifetime of the mortgage. We calculate each household's simulated interest payments over the lifetime of both mortgage alternatives, under all three sets of assumptions concerning FRM refinancing behavior, and estimating the probability that the homeowner sells the house and moves based on head of household age. Finally, we use households' actual choice probabilities from Table 4 (including the actual origination year interest rates), with the coefficient on inflation experiences turned on and turned off, to calculate the WRTE. The point of this exercise is to hold household's initial choices and switching probabilities fixed, and to understand the range of possible *ex post* realizations that might plausibly have occurred under different inflation environments.

We simulate the following features of the economic environment, summarized in Table 11:

- **Inflation** follows an AR(1) process: $\pi_t = \mu + \phi(\pi_{t-1} - \mu) + \epsilon_{\pi,t}$ with serially-independent innovations $\epsilon_{\pi,t} \sim$ indep. $\mathcal{N}(0, (1-\phi^2)\sigma_\pi^2)$.

- One-year log **real interest rates** are serially uncorrelated: $r_t = \rho + \epsilon_{r,t}$, with $\epsilon_{r,t} \sim$ indep. $\mathcal{N}(0, \sigma_r^2)$ that are mutually-independent to the inflation innovations: $\epsilon_{r,\cdot} \perp \epsilon_{\pi,\cdot}$.

- Nominal log interest rates:

  - **Short-term nominal rates** equal the real interest rate plus actual inflation: $y_t^1 = r_t + \pi_t$.

– **Long-term nominal rates** follow the expectations hypothesis with a term premium:

$$y_t^T = \frac{1}{T}\sum_{s=1}^{T} \mathbb{E}_t y_{t+s-1}^1 + \theta^T$$

where $\mathbb{E}_t y_{t+s}^1 = \rho + \phi^s(\pi_t - \mu) + \mu$.

- **ARM rates** equal the one-year nominal bond rate plus a term premium:

  – ARM teaser rate (in year 1) is $y_1^A = y_t^1 + \theta^{A,1}$;

  – ARM reset rate (years 2-30) is $y_t^A = y_t^1 + \theta^A$.

- The **FRM rate** (all years) equals the ten-year nominal bond rate plus a term premium: $y_t^F = y_t^{10} + \theta^F$.

There are two independent sources of variation in each simulation: the sequences of inflation rates and of one-year real interest rates. All other variables are derived by exact, linear relationships.

The inflation process parameters are based on fitting an AR(1) model to CPI-U log inflation over 1960-2013. We estimate an autoregression parameter of 0.733 and a long-run mean of 0.038. We set the term premium to 1 percentage point, the average yield spread between ten-year and one-year constant maturity U.S. Treasuries for the same years. We estimate the mortgage premia using the average spreads between Freddie Mac PMMS national rates and constant maturity U.S. Treasuries over all available years between 1960 and 2013. This gives an initial ARM premium of 1.5 percentage points and a reset margin of 2.75 percentage points over the one-year Treasury. The FRM carries an average premium of 1.7 percentage points over the ten-year Treasury. Finally, we use the same parameterization as Campbell and Cocco (2003) to model the one-year real interest rate as a serially-uncorrelated process with mean equal to 2 percentage points and a standard deviation of 2.2 percentage points.

Figure 11 shows the results of 100 independent simulations. In each panel, we plot the WRTE on the vertical axis against either an initial or a 30-year average characteristic of the economic environment, along with univariate lines of best fit. The two left panels show that the WRTE is inversely correlated with inflation, both in the origination year and averaged over the 30-year mortgage term. This is consistent with the idea that FRMs provide insurance against high inflation environments. In simulations with 30-year average inflation exceeding about 4%, the WRTE becomes negative, indicating that the FRM is *ex post* cheaper. The two right panels show that the FRM is *ex post* more costly in simulations when the FRM-ARM spread is higher, again as expected.

The dotted lines mark the average value of each variable during the RFS sample period. This helps indicate whether the actual costs are "unusual" relative to the distribution of possible economic environments. For example, given year 1 inflation of 3.4% (a little below μ), we would expect to observe a WRTE of approximately \$1,500; in the actual data the WRTE is a little over \$8,000. This difference is mostly explained by the fact that average inflation over 1986-2013 declined to 2.8%, a full percentage point below our parameterization of μ. In simulations with similarly low values of average inflation over a 30-year period, we estimate WRTEs of approximately \$5,500.

Table 12 reports estimates of multivariate relationships between simulated WRTE, inflation, and the FRM-ARM spread, for all three sets of assumptions concerning FRM refinancing behavior, by OLS. The bottom two rows report multivariate predicted values and standard errors. As suggested by the scatter plots, FRMs were unusually *ex post* expensive given initial economic conditions, but not given subsequent economic conditions. Columns 4-6 indicate that every additional percentage point of average inflation over the lifetime of the mortgage reduces the *ex post* cost of the FRM by over \$4,000 in the simulated data. The rapid decline in inflation to its pre-Great Inflation levels, about one percentage point below its 1960-2013 average, thus explains about half of our *ex post* cost estimates in the actual data (\$5,500 - \$1,500 = \$4,000 of the \$8,0000).

These calculations assume that inflation was expected to revert to a long-run mean of 3.8%, based on an historical average value that includes the Great Inflation period. However, U.S. inflation averaged only 2.8% over 1986-2013. This is almost identical to the average level of inflation during the post-war, pre-Great Inflation years of 1946-67. Given economic conditions in the mid-1980s but taking a longer-run perspective, the low-inflation experience of the 1990s was perhaps less surprising than our simulation assumes. This is of course precisely the point we argue throughout the paper: overweighting recent experiences can be costly.

5 Conclusion

This paper shows that higher lifetime inflation experiences significantly increase the probability of a household taking out a fixed-rate mortgage, consistent with the theory that householders perceive the risk of future nominal interest rate hikes as greater and are demanding greater insurance against these hikes. We estimate that this bias is the determining factor in choosing an FRM for between 15 and 20 percent of outstanding mortgages, and that the mistake is costly. Householders exhibit an *ex ante* willingness to pay of between 6 and 21 basis points on the FRM mortgage contract. *Ex post* (as of the RFS survey year), the average switching household would have been better off by nearly \$3,000 in present value terms if it had chosen an ARM. This figure rises to over \$8,000 after accounting for expected refinancing behavior and years of occupancy in the home.

Let's put these numbers in an aggregate perspective: The 2001 RFS reports that there were approximately 36 million one-unit, homeowner-occupied, mortgaged properties. Accounting for second and third mortgages on some of these properties, this translates into 46 million mortgages. Based on a historical average of 80% FRM market share, 36.8 million of these mortgages would be fixed-rate and 9.2 million would be adjustable-rate. Our estimates from Scenario 3 indicate that experienced inflation raises the FRM share by 16.4 percentage points. So, we estimate that 7.5 million fixed-rate mortgage choices were marginal and would switch to an ARM if the householder did not overweight experienced inflation. At a present value cost of \$8,391 (after-tax, year 2000) per mortgage over its time of occupancy, times 7.5 million mortgages, this indicates that households were overpaying by \$63.3 billion. The value of the aggregate one-unit, owner-occupied mortgaged housing stock was approximately \$6.5 trillion in 2001, so the aggregate dollar cost is a little less than 1% of the value of aggregate housing stock.

References

Agarwal, S., I. Ben-David, and V. Yao (2017). Systematic mistakes in the mortgage market and lack of financial sophistication. *Journal of Financial Economics 123*(1), 42–58.

Agarwal, S., J. C. Driscoll, and D. Laibson (2013). Optimal Mortgage Refinancing: A Closed Form Solution. *Journal of Money, Credit and Banking 45*(4), 591–622.

Agarwal, S., R. J. Rosen, and V. Yao (2015). Why Do Borrowers Make Mortgage Refinancing Mistakes? *Management Science 62*(12), 3494–3509.

Alesina, A. and N. Fuchs-Schundeln (2007). Good-bye Lenin (or Not?): The Effect of Communismon PeopleÂ¡Â¯s Preferences. *American Economic Review 97*, 1507–1528.

Alm, J. and J. R. Follain (1982). Alternative Mortgage Instruments, the Tilt Problem, and Consumer Welfare. *Journal of Financial and Quantitative Analysis 19*(1), 113–126.

Andersen, S., J. Y. Campbell, K. M. Nielsen, and T. Ramadorai (2015). Inattention and inertia in household finance: Evidence from the Danish mortgage market. Working Paper, National Bureau of Economic Research.

Baesel, J. and N. Biger (1980). The Allocation of Risk: Some Implications of Fixed Versus Index-Linked Mortgages. *Journal of Financial and Quantitative Analysis 15*(2), 457–468.

Bajo, E. and M. Barbi (2015). Out of Sight, Out of Mind: Financial Illiteracy and Sluggish Mortgage Refinancing.

Bennett, P., R. Peach, and S. Peristiani (2000). Implied Mortgage Refinancing Thresholds. *Real Estate Economics 28*(3), 405–434.

Brueckner, J. and J. Follain (1988). The Rise and Fall of the ARM: An Econometric Analysis of Mortgage Choice. *The Review of Economics and Statistics 70*(1), 93–102.

Brueckner, J. K. (1992). Borrower Mobility, Self-Selection, and the Relative Prices of Fixed- and Adjustable-Rate Mortgages. *Journal of Financial Intermediation 2*(4), 401–421.

Brueckner, J. K. (1994). Borrower mobility, adverse selection, and mortgage points. *Journal of Financial Intermediation 3*(4), 416–441.

Campbell, J. Y. (2013). Mortgage Market Design. *Review of Finance 17*(1), 1–33.

Campbell, J. Y. and J. F. Cocco (2003, November). Household Risk Management and Optimal Mortgage Choice. *The Quarterly Journal of Economics 118*(4), 1449–1494.

Campbell, J. Y. and J. F. Cocco (2015). A model of mortgage default. *The Journal of Finance 70*(4), 1495–1554.

Chambers, M. S., C. Garriga, and D. Schlagenhauf (2009, July). The Loan Structure and Housing Tenure Decisions in an Equilibrium Model of Mortgage Choice. *Review of Economic Dynamics 12*(3), 444–468.

Dhillon, U. S., J. D. Shilling, and C. F. Sirmans (1987). Choosing Between Fixed and Adjustable Rate Mortgages. *Journal of Money, Credit and Banking 19*(2), 260–267.

Dunn, K. B. and C. S. Spatt (1988). Private information and incentives: Implications for mortgage contract terms and pricing. *The Journal of Real Estate Finance and Economics 1*(1), 47–60.

Dynarski, M. (1985). Housing demand and disequilibrium. *Journal of Urban Economics 17*(1), 42–57.

Follain, J. (1990). Mortgage Choice. *Real Estate Economics 18*(2), 125–144.

Green, J. and J. B. Shoven (1986). The Effects of Interest Rates on Mortgage Prepayments. *Journal of Money, Credit and Banking 18*(1), 41.

Green, R. K. and M. LaCour-Little (1999). Some Truths about Ostriches: Who Doesn't Prepay Their Mortgages and Why They Don't. *Journal of Housing Economics 8*, 233–248.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica 47*(1), 153–161.

Heckman, J. (1990). Varieties of Selection Bias. *American Economic Review 80*(2), 313–318.

Heckman, J. J. and E. J. Vytlacil (2007). Chapter 71 Econometric Evaluation of Social Programs, Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and to Forecast their Effects in New Environments. *Handbook of Econometrics 6*(07), 4875–5143.

Hertwig, R., G. Barron, E. U. Weber, and I. Erev (2004). Decisions from Experience and the Effect of Rare Events in Risky Choice. *Psychological Science 15*, 534–539.

Kaustia, M. and S. Knüpfer (2008). Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions. *Journal of Finance 63*, 2679–2702.

Kearl, J. R. (1979). Inflation, Mortgages, and Housing. *Journal of Political Economy 87*(5), 1115–1138.

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

Koijen, R. S., O. V. Hemert, and S. V. Nieuwerburgh (2009, August). Mortgage Timing. *Journal of Financial Economics 93*(2), 292–324.

Lee, L.-F. (1978). Unionism and Wage Rates: A Simultaneous Equations Model with Qualitative and Limited Dependent Variables. *International Economic Review 19*(2), 415–433.

Luce, R. D. and P. Suppes (1965). Preferences, Utility, and Subjective Probability. In *Handbook of Mathematical Psychology*. New York: Wiley.

MacDonald, G. and T. Holloway (1996). Early Evidence on Balloon Performance. *The Journal of Real Estate Finance and Economics 12*(3), 279–293.

Malmendier, U. and S. Nagel (2011, April). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? *The Quarterly Journal of Economics 126*(1), 373–416.

Malmendier, U. and S. Nagel (2016). Learning from inflation experiences. *The Quarterly Journal of Economics 131*(1), 53–87.

Malmendier, U., D. Pouzo, and V. Vanasco (2015). A Theory of Experience Effects. Working paper, UC-Berkeley.

Malmendier, U. and L. S. Shen (2015). Experience Effects in Consumption. Working paper, UC-Berkeley.

Malmendier, U. and A. Steiny (2016). Rent or buy? the role of lifetime experiences of macroeconomic shocks within and across countries. Working Paper, Working Paper.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*, pp. 105–142. New York: Academic Press.

Newey, W. K. (2009, January). Two-Step Series Estimation of Sample Selection Models. *Econometrics Journal 12*, S217–S229.

Powell, J. L. (1984). Least Absolute Deviations Estimation for the Censored Regression Model. *Journal of Econometrics 25*(3), 303–325.

Quigley, J. M. (1987). Interest Rate Variations, Mortgage Prepayments and Household Mobility. *Review of Economics and Statistics 69*(4), 636–643.

Rubin, D. B. (1976, December). Inference and Missing Data. *Biometrika 63*(3), 581–592.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: John Wiley & Sons.

Sa-Aadu, J. and C. F. Sirmans (1995). Differentiated Contracts, Heterogeneous Borrowers, and the Mortgage Choice Decision. *Journal of Money, Credit and Banking 27*(2), 498.

Scrimgeour, D. (2008). The Great Inflation Was Not Asymmetric: International Evidence. *Journal of Money, Credit and Banking*, 799–815.

Stanton, R. (1995). Rational Prepayment and the Value of Mortgage-Backed Securities. *Review of Financial Studies 8*(3), 677–708.

Stanton, R. and N. Wallace (1998). Mortgage Choice: What's the Point? *Real Estate Economics 26*(2), 173–205.

Train, K. (2009). *Discrete Choice Methods with Simulation* (Second edition). Cambridge: Cambridge UP.

Tversky, A. and D. Kahneman (1974). Judgment Under Uncertainty: Heuristics and Biases. *Science 4157*, 1124–1131.

Weber, E. U., U. Bockenholt, D. J. Hilton, and B. Wallace (1993). Determinants of Diagnostic Hypothesis Generation: Effects of Information, Base Rates, and Experience. *Journal of Experimental Psychology: Learning, Memory, and Cognition 19*, 1151–1164.

Figure 1.

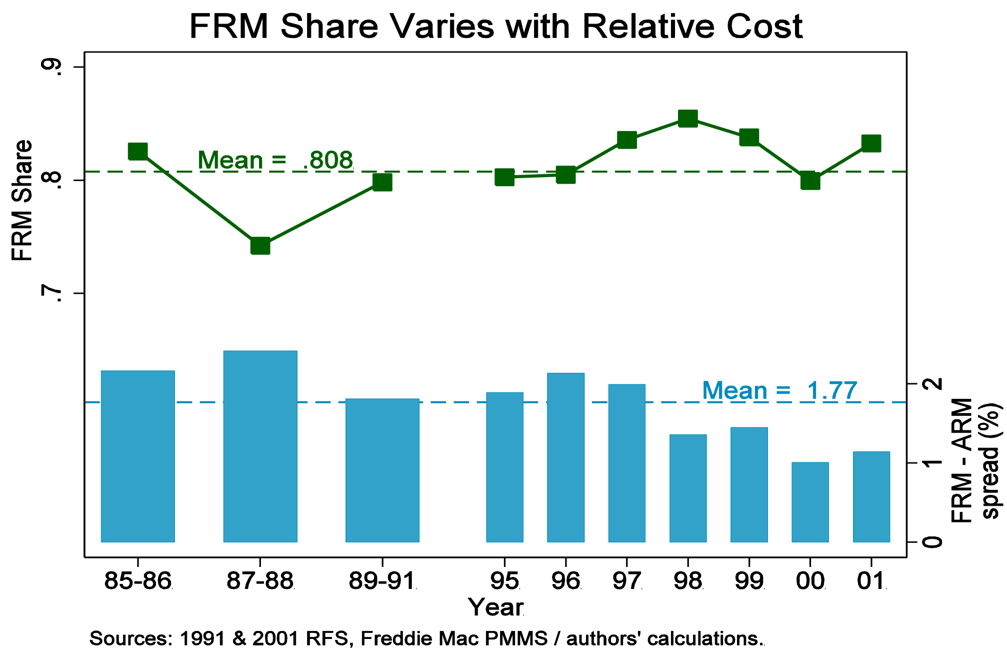

FRM Share Varies with Relative Cost
FRM Share
.9
.8
.7
Mean = .808
Mean = 1.77
2
1
0
FRM - ARM
spread (%)
85-86
87-88
89-91
95
96
97
98
99
00
01
Year
Sources: 1991 & 2001 RFS, Freddie Mac PMMS / authors' calculations.

Figure 2.

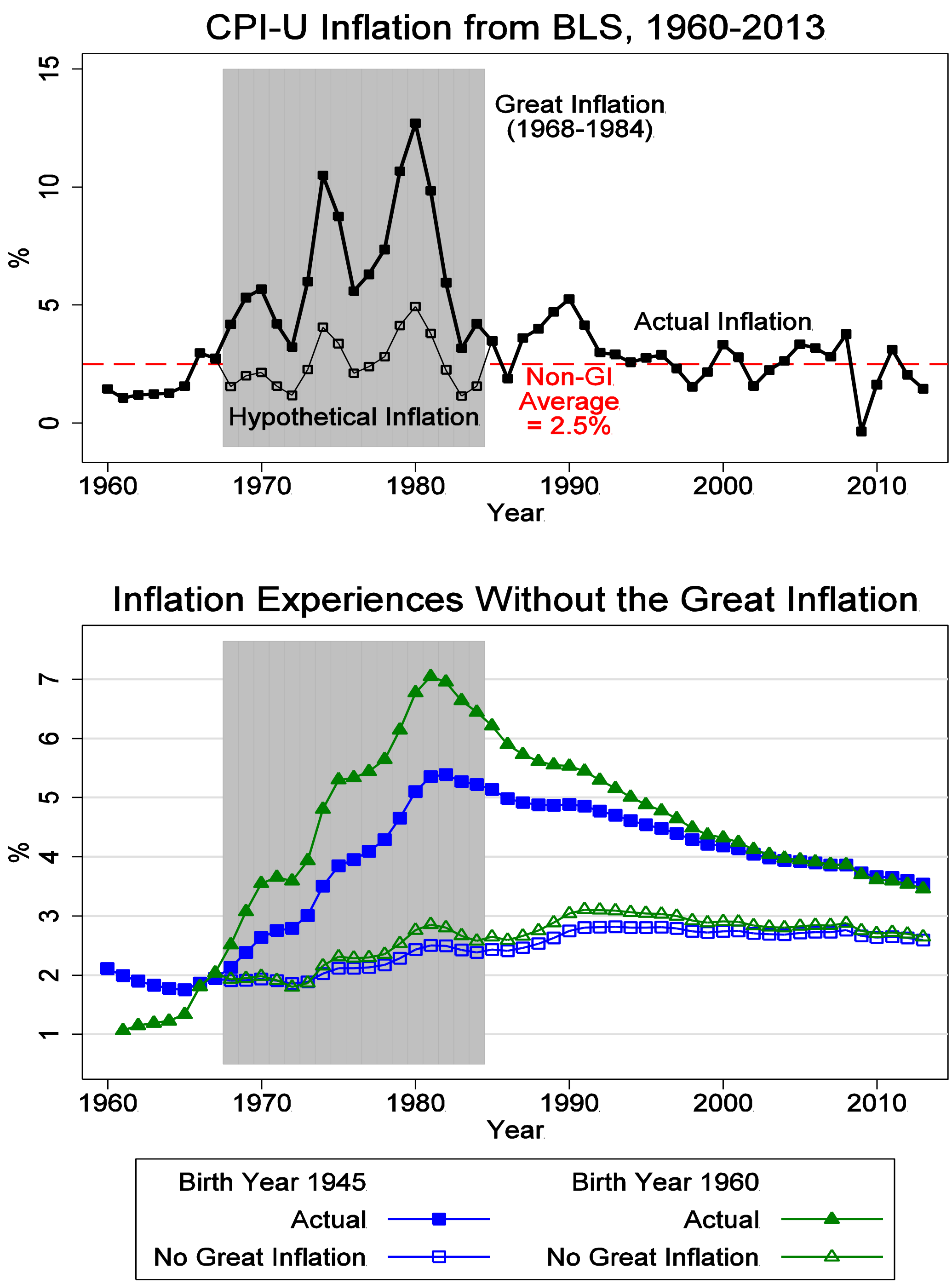

CPI-U Inflation from BLS, 1960-2013
Great Inflation
(1968-1984)
Actual Inflation
Non-GI
Average
= 2.5%
Hypothetical Inflation
%
Year
Inflation Experiences Without the Great Inflation
%
Year
Birth Year 1945
Actual
No Great Inflation
Birth Year 1960
Actual
No Great Inflation

Figure 3: Individuals with Higher Inflation Experiences Are More Likely to Expect Interest Rates to Rise

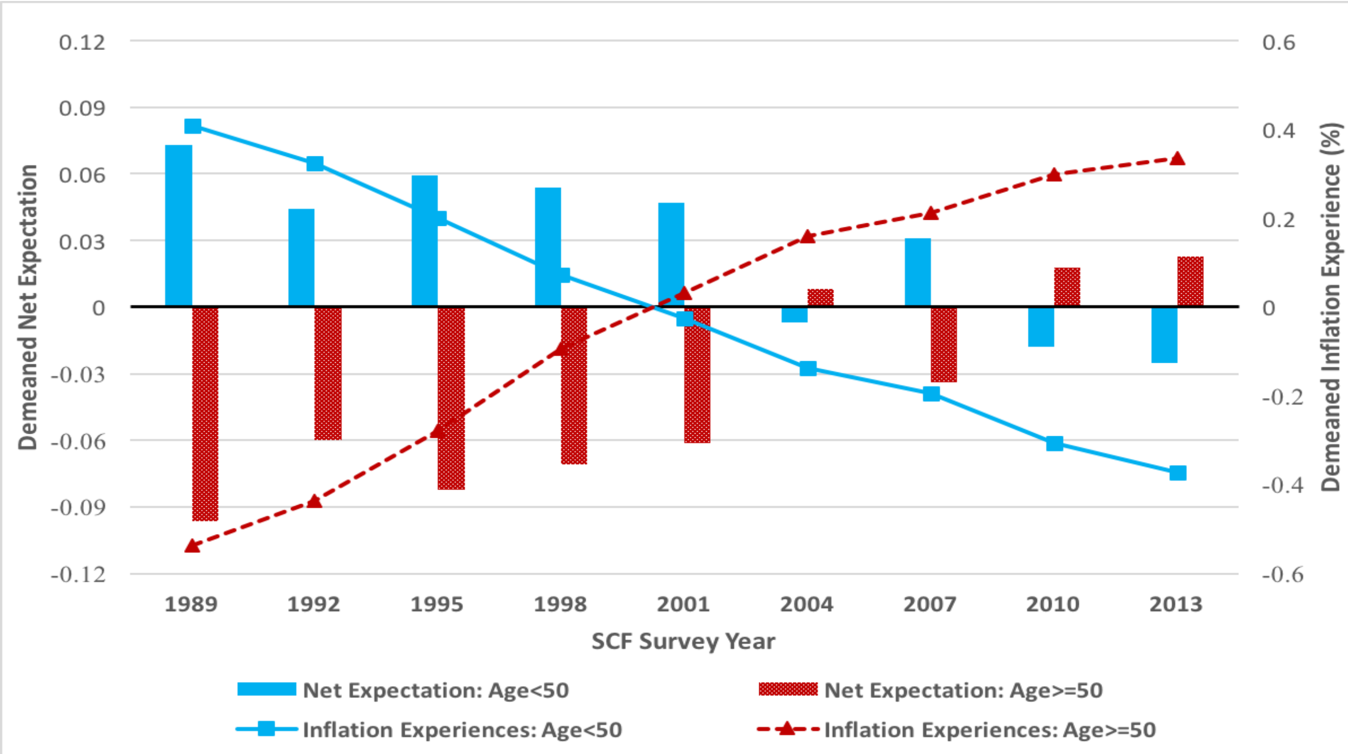


Figure 4.

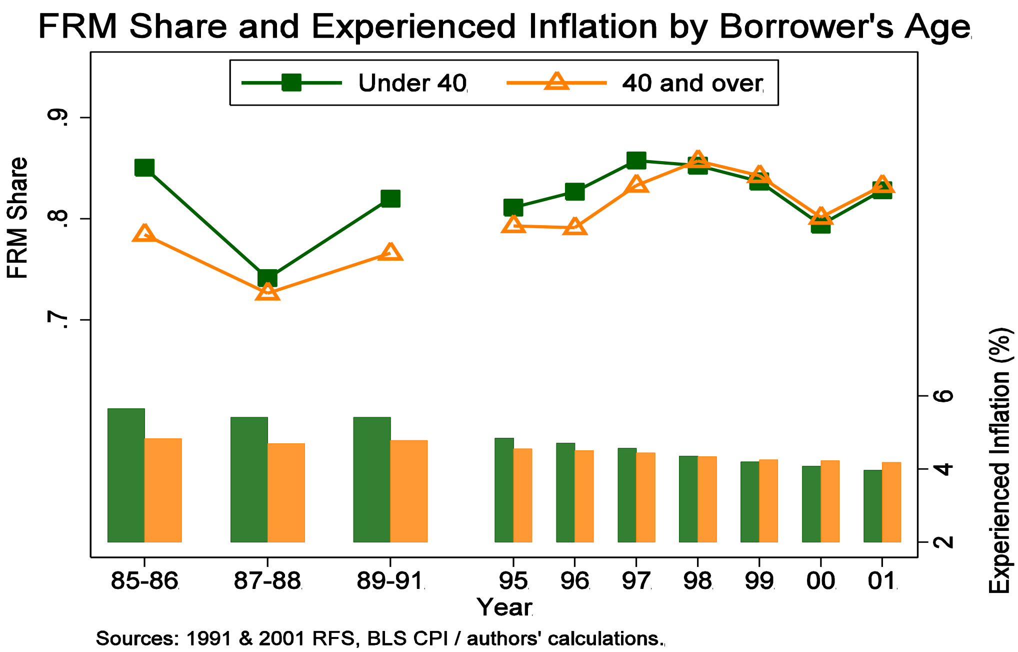
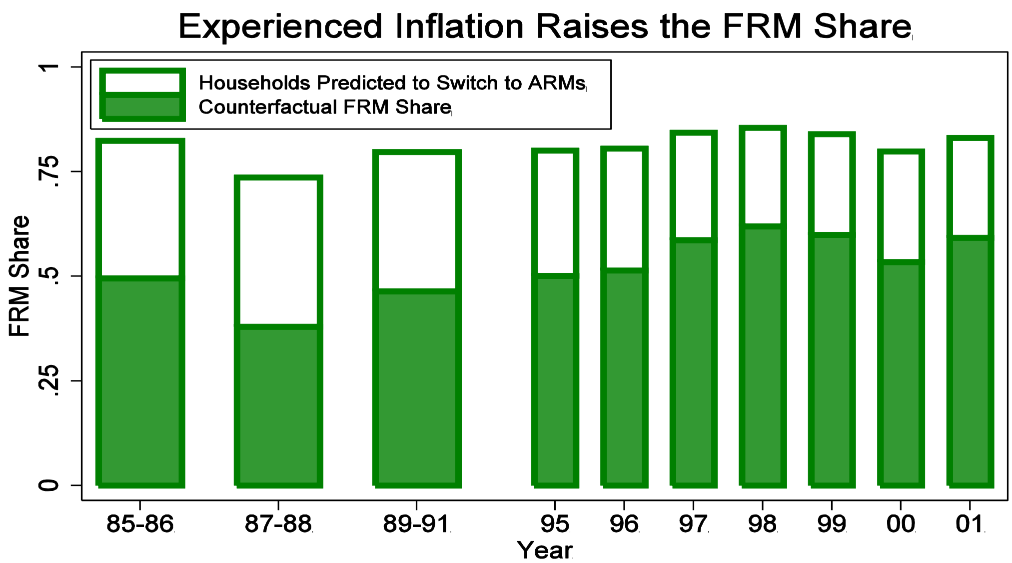

FRM Share and Experienced Inflation by Borrower's Age
Under 40
40 and over
FRM Share
.9
.8
.7
Experienced Inflation (%)
6
4
2
85-86
87-88
89-91
95
96
97
98
99
00
01
Year
Sources: 1991 & 2001 RFS, BLS CPI / authors' calculations.

Figure 5.



Source: 1991 & 2001 RFS / authors' calculations.

Counterfactual uses estimates from Table 2 column 3, with coefficient on experienced inflation set to zero.

Figure 6.

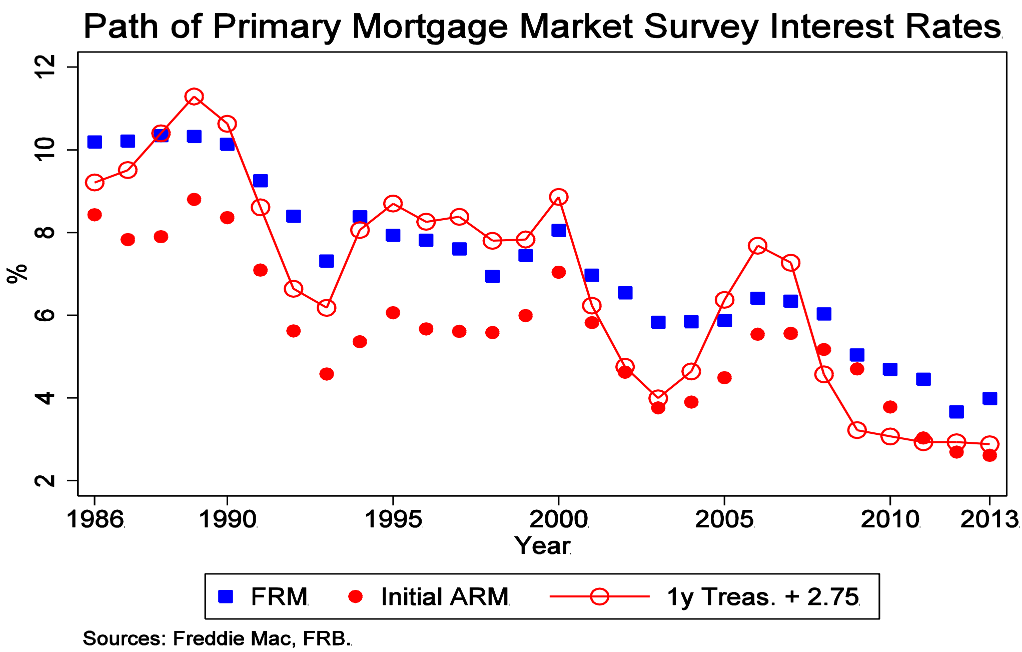
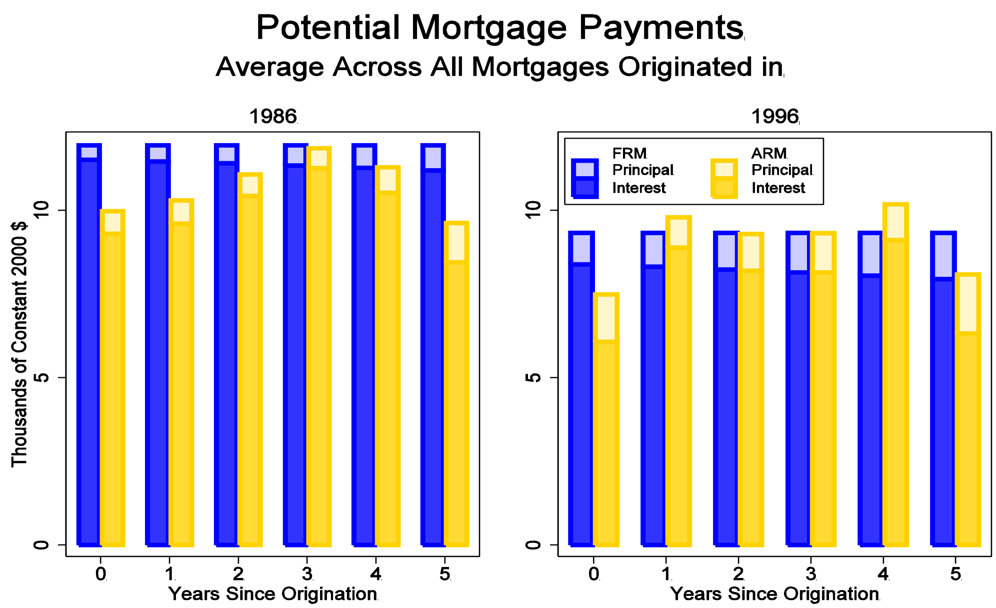
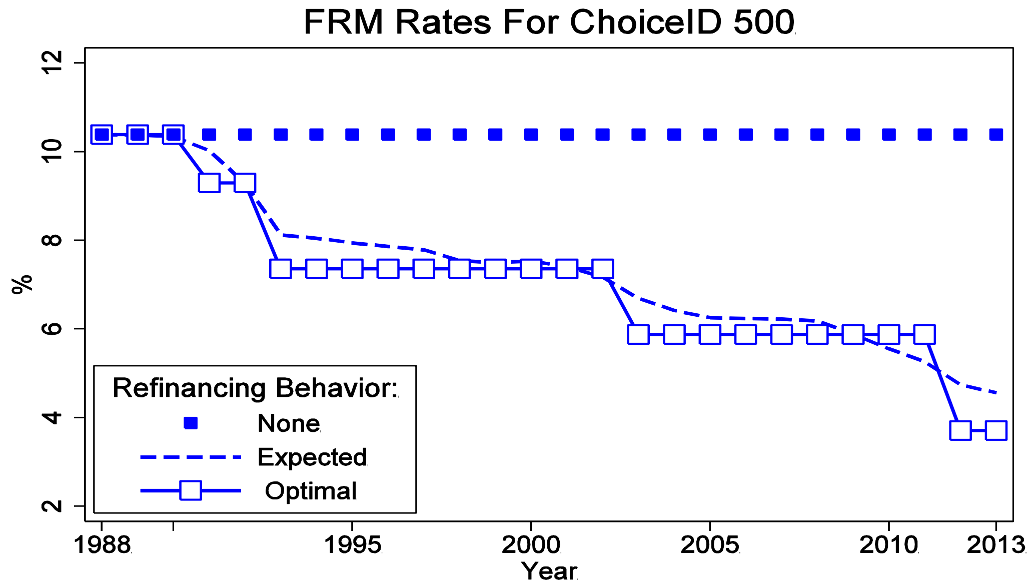

Path of Primary Mortgage Market Survey Interest Rates
%
12
10
8
6
4
2
1986
1990
1995
2000
2005
2010
2013
Year
FRM
Initial ARM
1y Treas. + 2.75
Sources: Freddie Mac, FRB.

Figure 7.



Based on PMMS rates and 2.75 p.p. margin over 1-year Treasury, with annual resets and no caps.
(Balloon mortgages omitted.)

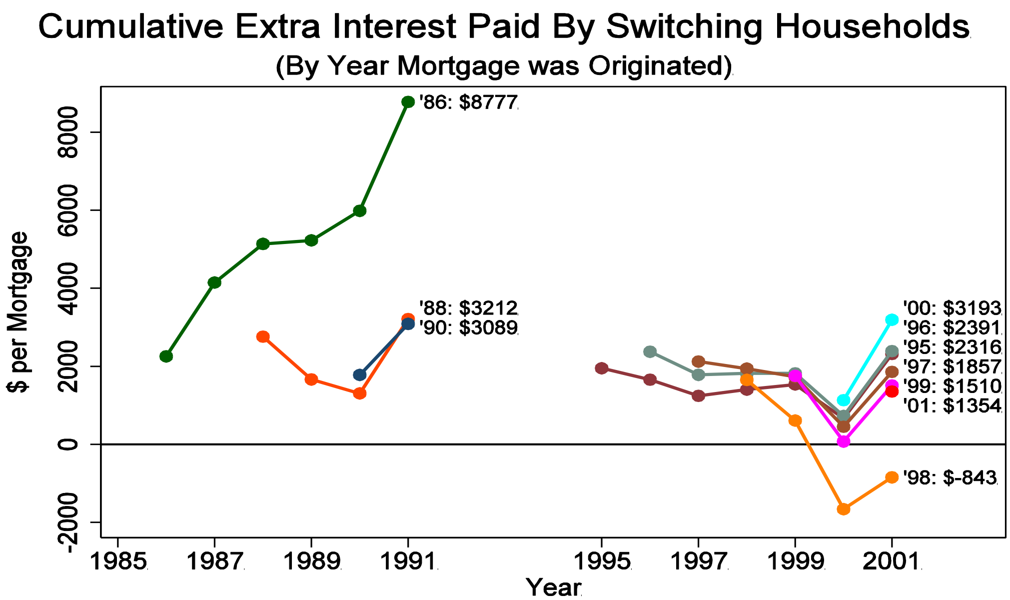
Figure 8.



Source: 1991 RFS / authors' calculations.

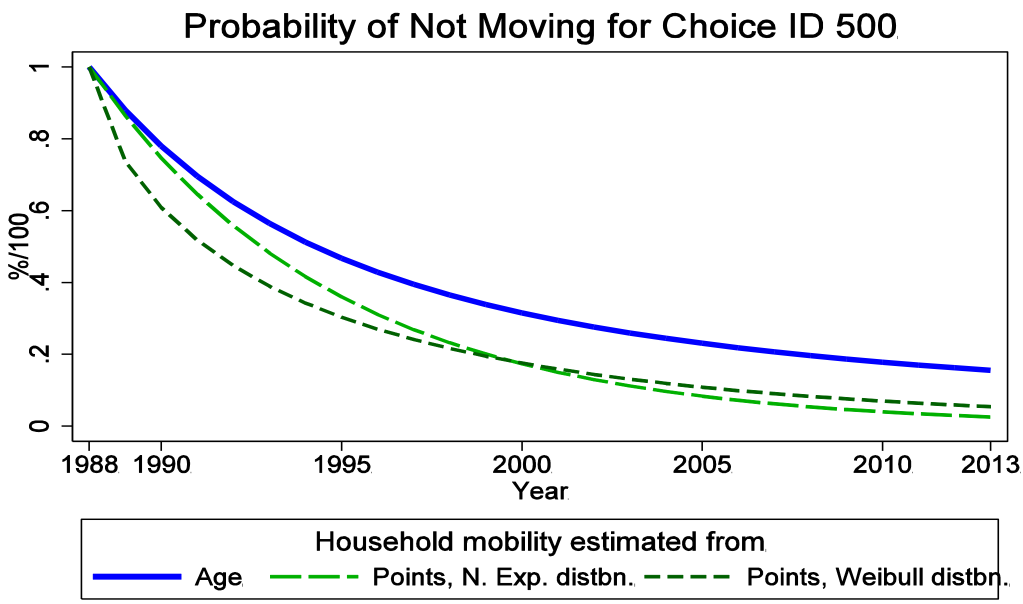
Refinancing behavior described in notes to Tables 6 and 7.

Figure 9.



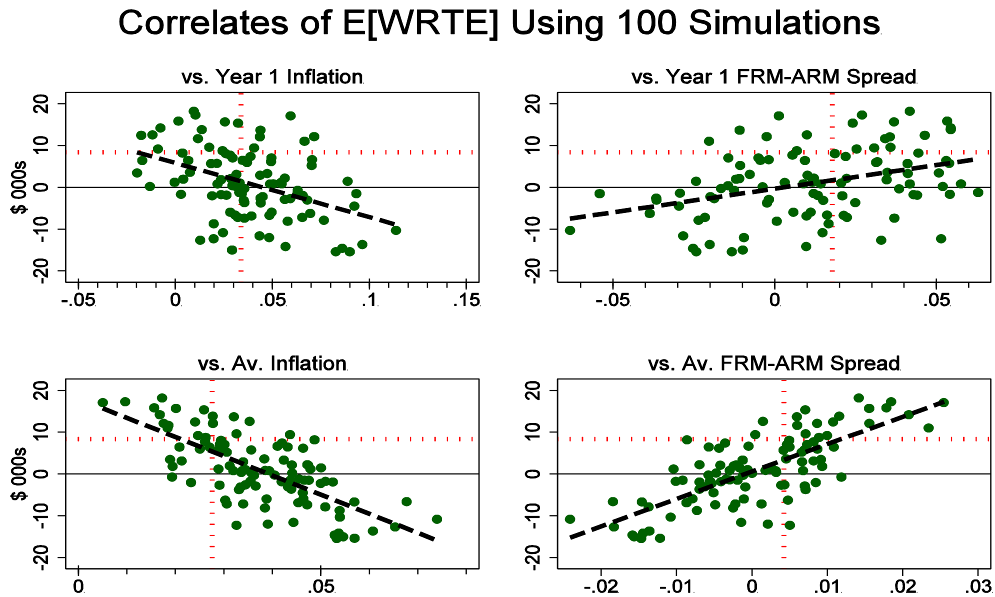
Based on Scenario 1: PMMS rates and 2.75 p.p. margin over 1-year Treasury, with annual resets and no caps. Choice probabilities from Table 2, column 3.

Figure 10.



Head of household was 30 in 1988, and paid 3 discount points at time of origination.
Time to break even is 83 months (=6.9 years), discounting at 8% / year.

Figure 11.



Estimates based on Scenario 3 estimates & age-based mobility. Dotted lines indicate average values during RFS sample period (origination years or 1986-2013).

Table 1: Summary Statistics

Sample of mortgages originated ≤ 6 years ago at time of 1991 and 2001 Residential Finance Surveys of homeowner properties, with primary borrower between 25 and 74 years old at origination. Statistics are based on available cases. * $p<0.05$.

	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.
Seasoning (years)	2.6	2.8	2.1	-0.2*
Term (years)	23.2	26.1	8.9	-2.9*
Prepayment penalty?	0.061	0.091	0.058	0.0*
Economic Conditions (all in %)				
Inflation	3.36	3.47	3.64	-0.11*
FRM - ARM spread	1.75	1.86	1.69	-0.11*
Default spread	2.09	2.09	2.06	0.00
Yield spread	0.90	0.99	0.84	-0.09*
Borrower Characteristics				
Primary owner age	41.4	41.8	42.8	-0.4
Experienced inflation (%)	4.74	4.79	4.68	-0.05*
Nonwhite?	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 $)	72,381	81,231	68,674	-8,850*
Property Characteristics				
Central city of MSA?	0.257	0.258	0.214	0.000
Outside MSA?	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*
Nonconventional?	0.197	0.057	0.039	0.140*
Refi?	0.256	0.244	0.294	0.012
Loan / income	1.80	2.13	1.61	-0.33*
Loan / value × 100	81.4	89.7	79.8	-8.2*
Loan / CLL	0.409	0.540	0.350	-0.130*
Jumbo loan?	0.043	0.127	0.056	-0.084*
Points paid (bps)	39.6	42.1	14.9	-2.5
Has buydown?	0.033	0.032	0.003	0.001

Notes.

Prepayment penalty clause only available for 1991. Investment income, second home status, and buydown indicator only available for 2001.

"Default spread" = Moody's seasoned corporate BAA - 10 year CM Treasury.

"Yield spread" = 10 year CM Treasury - 1 year CM Treasury.

Table 2: Reduced Form Logit Model of Mortgage Choice

Cols. 1-4 report multinomial logit coefficient estimates of choice among FRM, Balloon, and ARM in the 1991 and 2001 RFS for mortgages originated ≤ 6 years ago. Col 5 reports binomial logit coefficients between FRM and ARM, excluding balloon alternative. Omitted category for sociodemographic variables is ARM.

	(1)	(2)	(3)	(4)	(5)
Freddie Mac PMMS index	-0.483**				
rate (%)	(0.246)				
FRM Alternative-Specific Characteristics					
Freddie Mac PMMS FRM		-3.56***	-3.56***	-3.42***	-3.66***
index rate (%)		(0.591)	(0.591)	(0.609)	(0.829)
Experienced inflation in %	0.223**	0.22**	0.294***	0.263***	0.197**
	(0.096)	(0.096)	(0.086)	(0.088)	(0.098)
Log(Income)	-0.0070	-0.0063	-0.0064	0.0263**	0.0264**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	-0.0191	-0.0189	-0.0171	0.0172	0.0148
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Age^2	0.00021	0.00020	0.00020	-0.00016	-0.00015
	(0.00017)	(0.00017)	(0.00017)	(0.00018)	(0.00018)
ARM Alternative-Specific Characteristics					
Freddie Mac PMMS ARM		-0.861***	-0.865***	-0.784***	-0.856***
initial rate index (%)		(0.259)	(0.259)	(0.266)	(0.325)
Balloon Mortgage Alternative-Specific Characteristics					
Experienced inflation in %	-0.31*	-0.3040			
	(0.186)	(0.186)			
Log(Income)	-0.0344*	-0.0349*	-0.0352*	0.0080	
	(0.020)	(0.020)	(0.020)	(0.021)	
Age	-0.0196	-0.0204	-0.0182	-0.0283	
	(0.028)	(0.028)	(0.028)	(0.029)	
Age^2	0.00024	0.00025	0.00028	0.00030	
	(0.00030)	(0.00030)	(0.00030)	(0.00031)	
Number of Choice Situations	15,051	15,051	15,051	15,051	14,337
Log likelihood	-8829.6	-8811.4	-8812.9	-8367.2	-5708.5
$-\beta_{\pi,\text{ FRM}} / \beta_{\text{Rate, FRM}}$	0.462	0.062**	0.083***	0.077***	0.054*
(S.E. by delta method)	(0.309)	(0.029)	(0.028)	(0.029)	(0.030)
Alternative-specific constants	YES	YES	YES	YES	YES
Origination year FX	YES	YES	YES	YES	YES
Mortgage controls				YES	YES
Sociodemographic controls				YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
Separate coefficients for all mortgage / sociodemographic controls are estimated for each alternative.
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.

Table 3: Selection-Corrected Mortgage Rate Equations

Mortgages originated ≤ 6 years ago as of 1991 and 2001 Residential Finance Surveys, excluding balloon alternative. **Dependent variable = interest rate in bps.**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is:	FRM Rate		ARM Initial Rate		ARM Margin	
Estimation Method	CLAD	SSC CLAD	CLAD	SSC CLAD	CLAD	SSC CLAD
Freddie Mac PMMS index	83.73***	87.91***	76.16***	82.02***	0***	0
rate (%)	(0.79)	(1.95)	(3.58)	(7.27)	(0.00)	(0.00)
Log(Income)	-0.401	-0.859	-0.131	-0.67	0***	0
	(0.85)	(0.95)	(1.79)	(1.83)	(0.00)	(0.00)
First-time owner?	6.179***	5.826**	11.29	9.443	-0***	0
	(2.39)	(2.56)	(9.30)	(7.95)	(0.00)	(0.00)
Refi?	-25.03***	-28.16***	12.36	10.92	0***	0
	(2.93)	(3.96)	(9.99)	(10.10)	(0.00)	(0.00)
Junior mortgage?	165.6***	160.3***	171.3***	161.0***	25.00***	25.00***
	(10.20)	(10.00)	(22.90)	(20.10)	(0.00)	(0.00)
Nonconventional?	5.593**	-34.86**	-57.18***	-44.96	-0***	0
	(2.56)	(17.60)	(21.60)	(33.20)	(0.00)	(0.00)
Points paid (pctg points)	-0.963	-0.851	-6.307	-4.798	-0***	0
	(0.64)	(0.72)	(5.35)	(5.32)	(0.00)	(0.00)
Loan / CLL	-58.17***	-39.86***	-112.3***	-111.3***	-0***	0
	(6.01)	(11.10)	(16.30)	(18.80)	(0.00)	(0.00)
Jumbo loan?	38.72***	60.21***	60.51***	76.73***	0***	0
	(7.70)	(14.00)	(17.00)	(16.70)	(0.00)	(0.00)
Margin is indexed to COF Index					0***	0
					(0.00)	(0.00)
Margin is indexed to OTS or other					-0***	0
					(0.00)	(0.00)
Constant	158.6***		311.0***		275***	
	(11.70)		(29.10)		0.00	
Observations	12,051	12,051	1393	1393	1473	1473
Average Selection Bias		-49.34		14.92		0
Heckman (1990) estimate of constant		176		261.5		275

Robust / bootstrapped standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Notes:

CLAD: Censored Least Absolute Deviations, based on Powell (1984), accounts for top- and bottom-censoring of the dependent variable in survey public use files. Analytic robust SEs reported.

SSC: Semiparametric Selection Correction model, based on Newey (2009), uses 4th-order power series control functions in $2\Phi(xb)-1$ following first-stage probit in likelihood of being selected. Bootstrapped SEs (50 repetitions) reported.

Average Selection Bias is average value of the structural error term in the subsample choosing alternative *i* .

Heckman (1990) constant is estimated as average value of $b_0 = y - x'b_1$ in the subsample of observations with choice probabilities above the 90th percentile cutoff.

Table 4: Structural Logit Model of Mortgage Choice

Logit coefficients. **Dependent variable = 1 if FRM and 0 if ARM (balloon alternative is omitted).** Sample is individuals in 1991 and 2001 RFS with mortgages originated ≤ 6 years ago. Rates for both alternatives estimated by CLAD.

	(1)	(2)	(3)	(4)	(5)	(6)
Selection Correction?	No	Yes	No	Yes	No	Yes
FRM Rate Offered	0.770***	-1.065***	-0.265**	-1.036***	-0.789***	-0.482***
	(0.09)	(0.11)	(0.12)	(0.11)	(0.13)	(0.12)
Initial ARM Rate Offered	-0.361***	1.008***	1.029***	1.196***	0.524***	0.674***
	(0.07)	(0.09)	(0.12)	(0.09)	(0.13)	(0.10)
ARM Margin Offered			-2.922***	-1.171***	3.219***	3.332***
			(0.19)	(0.07)	(0.49)	(0.46)
Experienced inflation in %	0.249***	0.223**	0.231**	0.205**	0.203**	0.214**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Log(Income)	-0.00412	0.00374	-0.0503***	-0.0193	0.0729***	0.113***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Age	-0.0163	-0.0225	-0.0101	-0.00817	0.000924	0.0154
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age^2	0.000201	0.000212	0.000119	0.0000832	0.0000109	-0.000139
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Joint owners?	0.0681	0.105**	0.108**	0.126**	0.126**	0.165***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Outside MSA?	-0.149**	-0.313***	-0.210***	-0.249***	-0.206***	-0.277***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Nonconventional Dummy					3.616***	5.738***
					(0.26)	(0.58)
Number of Choice Situations	14,212	14,212	14,212	14,212	14,212	14,212
Pseudo R2	0.0242	0.0272	0.0438	0.0546	0.0603	0.063
$-\beta_{\pi, FRM} / \beta_{Rate, FRM}$	-0.323**	0.209**	0.873	0.197**	0.258*	0.444*
(S.E. by delta method)	(0.129)	(0.094)	(0.541)	(0.098)	(0.133)	(0.235)
Alternative-specific constants	YES	YES	YES	YES	YES	YES
Origination year FX	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (not corrected for predicted explanatory vars).
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Cohorts With Higher Lifetime Experiences of Inflation Hold Larger Fixed-Rate Mortgage Balances

OLS regressions of log per capita mortgage amounts on birth-year cohorts' inflation experiences as of survey or origination year.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Balances		**Recent Balances**		**Loan Amount**	
Dependent variable:	*Log(FRM)*	*Log(ARM)*	*Log(FRM)*	*Log(ARM)*	*Log(FRM)*	*Log(ARM)*
Experienced Inflation (%)	0.352***	0.0951	0.740***	0.284	0.308**	-0.171
	(0.06)	(0.13)	(0.15)	(0.23)	(0.14)	(0.20)
Log(Household Income)	0.523*	1.807*	0.084	-1.117	0.502***	0.607***
	(0.26)	(0.90)	(0.61)	(1.39)	(0.07)	(0.22)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Age Fixed Effects	YES	YES	YES	YES	YES	YES
As of	Survey Year	Survey Year	Survey Year	Survey Year	Orig. Year	Orig. Year
Sample	Homeowners	Homeowners	Homeowners	Homeowners	Mortgagors	Mortgagors
Observations	100	100	100	97	490	408
R-squared	0.99	0.89	0.96	0.86	0.57	0.29

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes.

[1] Each observation is a cohort - year average. Dependent variable is the natural log of per capita constant dollar mortgage amount in survey year (columns 1-4) or orignation year (columns 5-6). Log transformations are applied to per capita amounts. All amounts are deflated to constant year 2000 dollars using CPI-U.

[2] Mortgage holdings defined as follows:

Columns 1-2: outstanding mortgage balance as of survey year.
Columns 3-4: outstanding balance of mortgages financed ≤ 2 years prior to survey year.
Columns 5-6: original loan amount of mortgages financed ≤ 6 years prior to survey year.

[3] Sample is:

Columns 1-4: all homeowners with head of household between ages of 25 and 74 in survey year.
Columns 5-6: all mortgagors with head of household between ages of 25 and 74 in origination year.

Table 6: Refinancing Behavior for a Sample Household

This table illustrates optimal and expected refinancing behavior for a sample choice situation, choice ID 500 in our dataset (from the 1991 RFS). This joint-owner household took out a loan for $204,844 in 1988 on a property in the Midwest Census region. The head of household was 30 years old, and the household reported total income of $163,467. All dollar figures are in constant year 2000 units.

Year	Potential FRM Rates	Optimal Threshold (pp)	Probability of refinancing (%)	FRM Rate (%) No Refi	FRM Rate (%) Optimal Refi
1	10.38	0.94	0.0	10.38	10.38
2	10.36	0.94	13.7	10.38	10.38
3	10.17	0.95	16.0	10.38	10.38
4	9.29	0.95	30.4	10.38	9.29
5	8.43	0.96	43.2	10.38	9.29
6	7.35	0.96	51.2	10.38	7.35
7	8.42	0.97	13.3	10.38	7.35
8	7.97	0.98	16.4	10.38	7.35
9	7.85	0.99	15.6	10.38	7.35
10	7.64	1.00	16.7	10.38	7.35
11	6.98	1.01	25.2	10.38	7.35
12	7.48	1.03	14.1	10.38	7.35
13	8.09	1.04	7.7	10.38	7.35
14	7.01	1.06	19.7	10.38	7.35
15	6.58	1.08	24.1	10.38	7.35
16	5.87	1.11	33.1	10.38	5.87
17	5.88	1.14	24.2	10.38	5.87
18	5.91	1.17	18.8	10.38	5.87
19	6.45	1.21	10.0	10.38	5.87
20	6.38	1.25	9.9	10.38	5.87
21	6.07	1.31	12.0	10.38	5.87
22	5.08	1.38	23.8	10.38	5.87
23	4.73	1.46	23.9	10.38	5.87
24	4.49	1.56	21.3	10.38	5.87
25	3.70	1.70	27.5	10.38	3.70

Notes.

Potential FRM rates estimated from Freddie Mac PMMS rate in year and HH risk characteristics in survey year (Table 3 column 2).

Optimal Threshold for refinancing is the Agarwal et. al (2013) square-root rule.

The conditional probability of refinancing from previous interest rate i_0 to current rate i is based on Andersen et al. (2014) Table 8 column 1 -- $P(\text{refi} \mid i_0) = \Phi\{-1.921 + e^{-1.033} \times (i_0 - i - OT)\}$ -- converted from monthly to annual horizon. Table reports the unconditional probability of refinancing at begin--ning of each year.

Table 7: Interest Payments for a Sample Household

This table illustrates nominal mortgage payments under alternate refinancing scenarios for a sample household (choice ID 500 in our dataset). The loan was for $204,844 in constant 2000 $.

	FRM Interest Payments ($)			ARM	
Year	**No Refi**	**Expected Refi**	**Optimal Refi**	**Rate (%)**	**Interest ($)**
1	21,268	21,268	21,268	8.03	16,393
2	21,158	21,153	21,158	11.62	23,558
3	21,037	20,965	21,037	10.96	22,108
4	20,903	20,183	18,709	8.94	17,902
5	20,722	18,526	18,546	6.97	13,797
6	20,523	16,060	14,533	6.51	12,691
7	20,225	15,680	14,323	8.39	16,108
8	19,906	15,226	14,096	9.03	17,102
9	19,561	14,821	13,852	8.59	16,029
10	19,191	14,390	13,590	8.71	15,982
11	18,792	13,650	13,308	8.13	14,634
12	18,363	13,269	13,004	8.16	14,369
13	17,902	12,987	12,677	9.19	15,812
14	17,405	12,404	12,325	6.56	10,976
15	16,870	11,649	11,947	5.08	8,186
16	16,295	10,501	9,217	4.32	6,650
17	15,597	9,636	8,822	4.97	7,273
18	14,857	8,949	8,403	6.70	9,311
19	14,071	8,455	7,959	8.01	10,568
20	13,239	7,936	7,488	7.60	9,469
21	12,356	7,353	6,989	4.90	5,684
22	11,420	6,471	6,459	3.55	3,761
23	10,428	5,579	5,898	3.40	3,233
24	9,375	4,749	5,303	3.26	2,732
25	8,260	3,769	2,945	3.26	2,351
PDV	**215,079**	**176,855**	**170,892**		**167,949**
- Int. Deduct.	-53,770	-44,214	-42,723		-41,987
+ Refi Cost	0	4,705	3,895		0
Total	**161,310**	**137,346**	**132,064**		**125,962**

Notes.

"No Refi": the household holds the initial FRM until maturity.

"Expected Refi": the probability of refinancing every year is given by a probit function of the interest rate differential estimated in Andersen et al (2014) - see notes to Table 5. Timing of principal repayment is the same as in Optimal Refi scenario.

"Optimal Refi": the household refinances when the interest rate differential exceeds the Agarwal et al. (2014) square-root rule threshold.

PDV calculations assume a nominal discount rate of 8% / year ($r = .04$, $\pi = .04$).

The mortgage interest deduction is calculated assuming a 25% marginal tax rate. Refinancing costs $2,000 and is not tax-deductible.

Table 8: How Much Additional Interest Do Switching Households Pay Due to Inflation Experiences?

Table reports treatment effect on switching households, measured as the extra interest (after taxes) + refinancing costs paid by a household choosing an FRM instead of an ARM due to experienced inflation. Original loan amounts are in constant 2000 $.

Scenario 1: Primary Mortgage Market Survey rates

Time Horizon:	**Survey Year**	**5 years**	**10 years**	**20 years**	**E[tenure | age]**
After-tax PDV: (all in $)					
No Refi	2,227	5,063	10,267	21,064	11,462
Expected Refi	2,649	5,064	7,427	10,474	7,395
Optimal Refi	2,270	4,523	6,180	8,647	6,302
% switching households	18.3	18.3	18.3	22.0	18.3

Scenario 2: Risk-adjusted rates, seniority-adjusted ARM margins

Time Horizon:	**Survey Year**	**5 years**	**10 years**	**20 years**	**E[tenure | age]**
After-tax PDV: (all in $)					
No Refi	2,668	6,048	12,321	22,819	13,436
Expected Refi	3,095	6,005	9,273	11,813	9,107
Optimal Refi	2,705	5,438	7,964	9,940	7,960
% switching households	18.2	18.2	18.2	21.9	18.2

Scenario 3: Risk-adjusted rates and ARM margins

Time Horizon:	**Survey Year**	**5 years**	**10 years**	**20 years**	**E[tenure | age]**
After-tax PDV: (all in $)					
No Refi	2,383	5,720	11,708	22,585	12,976
Expected Refi	2,812	5,625	8,456	11,098	8,391
Optimal Refi	2,417	5,025	7,067	9,103	7,174
% switching households	16.4	16.4	16.4	19.6	16.4

Notes.

To calculate treatment effect on switching households, each household is weighted by the decline in probability of choosing an FRM contract when the experienced inflation coefficient is turned off in the choice model (Table 4, columns 2 and 6). Positive numbers indicate that the household overpaid and is worse off due to experienced inflation.

PDV calculations assume a nominal discount rate of 8% / year ($r = .04$, $\pi = .04$).

"No Refi," "Expected Refi," and "Optimal Refi" defined in notes to Tables 6.

The mortgage interest deduction is calculated assuming a 25% marginal tax rate. Refinancing costs $2,000 and is not tax-deductible.

Expected tenure estimated as a 4th-order polynomial of primary householder age from CPS ASEC.

Table 9: Additional Interest and Geographic Mobility

Table reports expected aditional interest paid by switching households, allowing for heterogeneity in probability of moving based on head of household's age or discount points paid. Original loan amounts are in constant 2000 $.

	(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: (all in $)					
No Refi	11,462	5,983	7,912	5,608	8,727
Expected Refi	7,395	4,808	5,810	4,371	5,986
Optimal Refi	6,302	4,187	5,000	3,832	5,152
Av. Median Tenure (years)	12.1	4.9	6.6	3.6	6.6
Scenario 2: Risk-adjusted rates, seniority-adjusted ARM margins					
After-tax PDV: (all in $)					
No Refi	13,436	6,955	9,233	6,441	10,119
Expected Refi	9,107	5,701	7,000	5,124	7,214
Optimal Refi	7,960	5,057	6,158	4,565	6,345
Av. Median Tenure (years)	12.1	4.8	6.6	3.6	6.6
Scenario 3: Risk-adjusted rates and ARM margins					
After-tax PDV: (all in $)					
No Refi	12,976	6,612	8,815	6,163	9,723
Expected Refi	8,391	5,275	6,452	4,765	6,661
Optimal Refi	7,174	4,598	5,563	4,177	5,742
Av. Median Tenure (years)	12.1	4.7	6.6	3.6	6.6

Notes.

Treatment effect, PDV calculations, and refinancing scenarios same as in Table 8.

Column (1): probability of moving every year estimated as a 4th-order polynomial of head of household's age based on 5-year migration / geographic mobility data from CPS ASEC 2005 and 2010.

Columns (2)-(5): discount points paid at time of origination used to calculate time to breakeven, τ^*, for each household, assuming an 8% nominal discount rate

Columns (2) & (3): time of moving events $\tau \sim$ Negative Exponential (λ) distribution, with λ picked to fit τ^* to the mean or median of distribution for each household.

Columns (4) & (5): time of moving events $\tau \sim$ Weibull (λ, 0.7) distribution, so the hazard rate of moving is decreasing over time. λ picked to fit τ^* to the mean or median of distribution for each household.

Median tenure calculated for each household, then averaged over all switching households.

Table 10: Additional Interest Under Different Inflation Environments

Table reports expected additional interest (after taxes) + refinancing costs paid by a household choosing an FRM instead of an ARM due to experienced inflation, using Scenario 3 predictions, with moving probabilities based on age. Original loan amounts are in constant 2000 $. **Positive numbers indicate that a household choosing an FRM overpaid and is worse off due to experienced inflation.**

Inflation Enviornment: **(Origination Year)**	***Baseline*** **(Actual)**	***Rising*** **(1971)**	***Falling*** **(1981)**
After-tax PDV: (all in $)			
No Refi	12,976	-14,591	35,395
Expected Refi	8,391	-13,216	10,299
Optimal Refi	7,174	-14,192	8,385

Notes.

Treatment effect, PDV calculations, and refinancing scenarios same as in Table 8, Scenario 3.

Probability of moving every year estimated as a 4th-order polynomial of head of household's age based on 5-year migration / geographic mobility data from CPS ASEC 2005 and 2010.

All 3 inflation environments use the household's actual lifetime inflation experiences, but simulate counter-factual, subsequent inflation histories. Baseline inflation environoment starts in the actual origination year (1988-1991 and 1995-2001). Rising inflation environment assumes that all mortgages were originated in 1971. Falling inflation environment assumes that all mortgages were originated in 1981.

FRM rates = historical Freddie Mac PMMS index + Scenario 3 risk adjustment. ARM initial rates = historical 1 year Treasury rate + 1.5 p.p. + Scenario 3 risk adjustment. ARM margin over 1-year Treasury rate based on Scenario 3 risk adjustment.

Table 11: 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	0.733	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

Notes.

Inflation follows an AR(1) process with normally-distributed innovations.

Real one-year interest rate innovations are independent, normally-distributed, and mutually-independent with the inflation innovations.

One-year nominal interest rates equal real rates plus inflation. Long-term rates are calculated via the expectations hypothesis.

PMMS data begin in 1971 for FRMs, and 1984 and '87 for ARMs.

Table 12: Is the FRM More Expensive in Simulated Data?

OLS regressions of Welfare Relevant Treatment Effect ($) on inflation and rate spread, across 100 simulations of N=14,212 households and T=30 years. Positive values indicate FRM is more expensive than ARM.

	(1)	(2)	(3)	(4)	(5)	(6)
Refi behavior:	*None*	*Expected*	*Optimal*	*None*	*Expected*	*Optimal*
FRM-ARM spread in origination year (%)	96.02	456.2	507.5	44.57	691.6***	758.6***
	(377)	(322)	(322)	(244)	(203)	(201)
Inflation in origination year (%)	-664.4	-969.0***	-985.7***			
	(411)	(344)	(342)			
Average inflation over mortgage's term (%)				-4992***	-4261***	-4222***
				(488)	(386)	(375)
Constant	43.57**	41.19**	27.85*	204.9***	160.5***	144.9***
	(20)	(17)	(17)	(21)	(16)	(16)
Simulations	100	100	100	100	100	100
R-squared	0.05	0.19	0.21	0.49	0.55	0.56
E[y| X=RFS values] ($)	**2,285**	**1,658**	**359**	**6,788**	**5,517**	**4,183**
S.E. of prediction	**(933.8)**	**(790.3)**	**(780.4)**	**(843.9)**	**(686.8)**	**(675.4)**

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes.

Simulation parameters described in Table 11.

All simulations use Scenario 3 mortgage rate predictions for each household and age-based mobility estimates. WRTE is calculated in present-value, after-tax terms using actual choice probabilities, with i=8% and τ=0.25.

A Mortgage Choice using the SCF

We pool together the full public data sets for every triennial SCF conducted between 1989 through 2013, merged with the summary extract public data sets to obtain each household's net worth. We keep information on the primary mortgage and any secondary mortgages on the principal residences, plus the first two reported mortgages on any secondary residences. Each mortgage enters as a separate observation in our analysis. Both income and net worth are deflated to constant, year 2013 dollars using the CPI-U-RS from BLS. We exclude a small number of households reporting negative values for income or net worth from the analysis. We include mortgages that were originated up to two years before the survey year for all the surveys except 1989; we extend the origination year back to 1985 for the 1989 SCF in order to match the time period with the RFS. (The 1986 survey differs in design from the later surveys, so is not directly comparable.) The longer time coverage in the SCF allows for more variations in the inflation experiences of different cohorts.

Appendix Table 1 reports estimates of the reduced-form binomial mortgage choice model, equation (4), including as many of the same controls as possible from Table 2, column 5. All of our point estimates use SCF sample weights, and we adjust the standard errors for multiple imputation using the standard Rubin (1987) formulas. Column 1 reports binomial logit coefficients for the full 1985-2013 time period, and column 2 restricts to the same origination years as the RFS: 1985-1991 and 1995-2001. Note that we cannot include the Freddie Mac PMMS rate indices since we do not observe geographic variation in borrower location, while time-series variation in the rate indices is absorbed by the year fixed effects.

Our estimate of the within-origination year effect of lifetime inflation experiences is remarkably similar: our point estimate for the logit index coefficient is between 0.250 and 0.325 (compared to 0.2 in Table 2, column 5). Given the much smaller sample sizes of the SCF surveys, our estimates are estimated less precisely. For example, the RFS has 60% more observations (= 14,337/8,929 - 1) than column 1, so we would expect the SCF standard error to be about 27% larger ($\sqrt{1.606} \approx 1.27$). The actual standard error in column 1 is 36% larger than in the RFS table (= 0.133/0.098 - 1). Despite the smaller sample, the coefficient on lifetime inflation experiences is statistically significant at the 10% level in column 1.

Appendix Table 1: Logit Model of Mortgage Choice using the SCF

This table reports binomial logit coefficients, adjusted for multiple imputations. **Dependent variable = 1 if FRM and 0 if ARM.** The sample is based on fixed / adjustable-rate mortgages originated between 1985 and 2013, using the most recent wave of the Survey of Consumer Finances (administered in 1989, 1992, 1995, ..., 2013.) Each observation is a mortgage, including primary and secondary mortgages on the principal residences and the primary and secondary mortgages on the secondary residences. Balloon mortgages are excluded.

	Origination year coverage **1985-2013**	Origination year coverage **1985-1991; 1995-2001**
Experienced inflation in %	0.253*	0.324
	(0.133)	(0.247)
Log(Income)	0.105	0.220*
	(0.073)	(0.131)
Log(Net worth)	-0.035	-0.088
	(0.043)	(0.067)
Joint owners? (=1 if the respondent is married)	0.087	-0.013
	(0.100)	(0.159)
Junior mortgage dummy	-0.199	0.296
	(0.126)	(0.198)
Nonconventional dummy	0.423***	0.340*
	(0.125)	(0.200)
Loan-to-CLL ratio	-0.188***	-0.163**
	(0.052)	(0.074)
Jumbo dummy (=1 if loan amount > CLL)	-0.758***	-0.648***
	(0.142)	(0.237)
Number of observations (per imputation)	8,929	3,161
Pseudo R2	0.079	0.073
Age controls	YES	YES
Origination year FE	YES	YES

Robust standard errors, adjusted for multiple imputations, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Notes.

Both regressions are estimated using SCF "revised consistent" sampling weights (variable X42001). The weights are scaled so that each survey wave receives equal weight.

We adjust for multiple imputations using the Rubin (1987) methodology:

- point estimates are the average of coefficients, estimated separately within each imputation.
- the multiple-imputation variance-covariance matrix, V, is

$$V = U + (1 + 1/M)\times B,$$

where U is the average within-imputation VCV matrix, B is the between-imputation VCV matrix, and M is the number of imputations (M = 5 in the SCF).

Income and net worth are adjusted for inflation. We drop obserations with negative values.

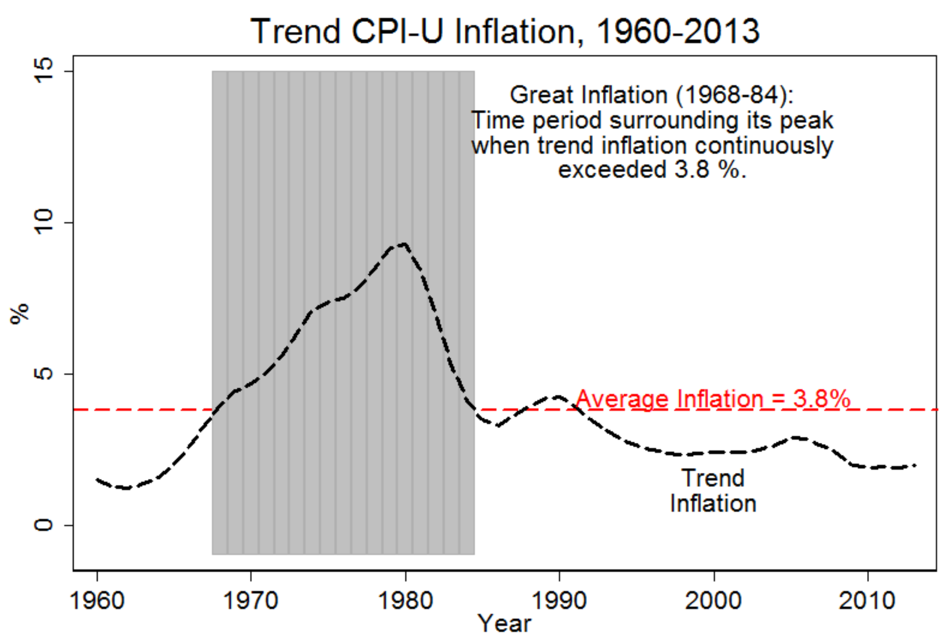
Loan/CLL is symmetrically Winsorized at the 1% level.

B 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 a triangular moving-average filter:

$$\pi_t^{trend} = \sum_{j=-h}^{h} \frac{h-|j|}{h^2} \pi_{t+h}, \tag{11}$$

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 U.S. 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.



Trend inflation calculated using a triangular filter with half-bandwidth = 4 years.