State Dependent Effects of Monetary Policy: The Refinancing Channel *

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Abstract

This paper studies how the impact of monetary policy depends on the distribution of savings from refinancing mortgages. We show that the efficacy of monetary policy is state dependent, varying in a systematic way with the pool of potential savings from refinancing. We construct a quantitative dynamic life-cycle model that accounts for our findings and use it to study how the response of consumption to a change in mortgage rates depends on the distribution of savings from refinancing. These effects are strongly state dependent. We also use the model to study the impact of a long period of low interest rates on the potency of monetary policy. We find that this potency is substantially reduced both during the period and for a substantial amount of time after interest rates renormalize.

Keywords: monetary policy, state dependency, refinancing.

JEL codes: E52, G21.

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1 Introduction

In the U.S., most mortgages have a fixed interest rate and no prepayment penalties. The decision to refinance depends on the potential savings relative to the refinancing costs. In this paper, we study how the impact of monetary policy depends on the distribution of savings from refinancing the existing pool of mortgages. We show that the efficacy of monetary policy is state dependent, varying in a systematic way with the pool of savings from refinancing.

We construct a quantitative dynamic life-cycle model that highlights new trade-offs in the design of monetary policy. These results are interesting to the extent that our model is a credible representation of the data. Our model has a number quantitative of properties that lend support to its credibility. First, it is consistent with the life-cycle dynamics of home-ownership rates, consumption of non-durable goods, household debt-to-income ratios and net worth. Second, it accounts for the probability that a mortgage is refinanced conditional on the potential savings from doing so. Third, and most importantly, the model accounts quantitatively for the state-dependent nature of the effects of monetary policy on refinancing decisions that we document in our empirical work.

We use our model to study how the impact of a decline in interest rates on consumption depends on the distribution of mortgage rates. One simple measure of the average savings from refinancing is the average gap between outstanding mortgages and current mortgage rates. When this gap is equal to the average value in the data, a 25 basis point drop in the mortgage rate leads to a 0.5 percent rise in consumption. In contrast, when this gap is one standard deviation above the mean, then consumption rises by 0.9 percent. So, our model implies strong state dependency in the response of consumption to a fall in mortgage rates.

We also use our model to study how the potency of monetary policy is affected by the history of interest rates. In response to the financial crisis, the Federal Reserve

kept interest rates low for an extended period of time. The potential benefits of this policy are widely understood (see e.g. Woodford (2012) and McKay, Nakamura and Steinsson (2016)). Our model points to a potentially important cost: it reduces the potency of monetary policy during the period of low interest rates as well as during the renormalization period and its aftermath. The size of these effects is substantial. In our model-based experiments when interest rates are below their steady-state values for six years, monetary policy is less potent for up to two years after renormalization.

Our work is related to a recent literature that stresses the importance of mortgage refinancing as a key channel through which monetary policy affects the economy. This literature discusses why the efficacy of monetary policy depends on the state of the economy because of supply-side considerations. For example, authors like Greenwald (2018) emphasize the importance of loan-to-value ratios and debt servicing-to-income ratios. Other authors focus on the effect of changes in house prices on the ability of households to refinance their mortgages. For example, Beraja, Fuster, Hurst, and Vavra (2018) show that regional variation in house-price declines during the Great Recession created dispersion in the ability of households to refinance.

In contrast to this literature, we focus on reasons why the efficacy of monetary policy depends on the state of the economy because of demand-side considerations, i.e. households' desire to refinance their mortgages. We certainly believe that supply-side constraints were very important in the aftermath of the financial crisis. But we also think that demand-side considerations were very important prior to the crisis and will become increasingly important as credit markets return to normal.

Our empirical results are closely related to contemporaneous, independent work by Berger, Milbradt, Tourre, and Vavra (2018). We view their work as complementary to ours. In contrast to these authors, we use a quantitative life-cycle model to study the impact of a lengthy period of low interest rates on the efficacy of monetary policy.

Our paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data used in our analysis. Section 4 discusses our measures of

potential savings from refinancing. Our basic empirical results are contained in Section 5. We present our quantitative life-cycle model of housing, consumption and mortgage decisions in Section 6. In Section 7, we show that our model can account for the state-dependent effects of monetary policy that we document on our empirical work. In addition, we use the model to study the state-dependent effects of monetary policy on consumption. Section 8 uses our model to study how the potency of monetary policy is affected an extended period of low interest rates and by a fall in refinancing costs. Section 9 provides some conclusions.

2 Related literature

Our paper relates to three strands of literature. The first strand is a large body of empirical work that studies consumption and refinancing responses to interest rate changes. This literature shows that households increase their expenditures when they reduce their mortgage payments and engage in cash-out refinancing (see, Beraja et al. (2018) and the references therein). In this paper, we extend the existing literature by showing that the effects of interest rate changes on refinancing and real outcomes depend on the distribution of mortgage rates. This type of state dependency differs from the state dependency based on loan-to-valuation constraints or home equity emphasized by Beraja et al. (2018).

The second strand of literature focuses on the role of the mortgage market in the transmission of monetary policy. Iacovello (2005), Garriga, Kydland and Sustek (2017) and Greenwald (2016) model the transmission mechanism using a representative borrower and saver model. In contrast, we use an heterogenous agent, life-cycle model that features transaction costs and borrowing constraints. Our model is related to work by Rios-Rull and Sanchez-Marcos (2008), Iacovelo and Pavan (2013), Berger, Guerrieri, and Lorenzoni (2017), Garriga and Hedlund (2017), Guren, Krishnamurthy, and McQuade (2017), Kaplan, Violante and Mittman (2017), Auclert (2017), Wong

(2018), Kaplan, Violante and Moll (2018), and Guren, McKay, Nakamura, and Steinsson (2018). In contrast to these papers, we focus on the state-dependent effects of monetary policy, and how these effects are shaped by past interest rate decisions made by the Federal Reserve.

The third strand of literature studies the distribution of mortgage rates across borrowers and emphasizes the role of transaction costs and inattention in explaining refinancing decisions. Examples include Bhutta and Keys (2016) and Andersen et al. (2018). In this paper, we extend the existing literature by studying how the distribution of mortgage rates leads to trade-offs in the conduct of monetary policy.

3 Data

Our empirical work is primarily based on Core Logic Loan-Level Market Analytics, a loan-level panel data set with observations beginning in 1995. These data include borrower characteristics (e.g. FICO and ZIP code) and loan-level information.[1] The latter includes the principal of the loan, the mortgage rate, the loan-to-value ratio (LTV), and the purpose of the loan (whether it refinances an existing loan or finances the purchase of a new house).

For each borrower, we obtain county-level demographic information including age structure, share of employment in manufacturing, lender competitiveness, measures of home-equity accumulation, educational attainment, unemployment, and per capita income. We describe these variables in Appendix A. We also obtain county-level housing permits from the Census Building Permits Survey and county-level unemployment rates from the CPS.

We use the Freddie Mac Single Family Loan-Level dataset to study cash-out refinancing, defined as instances in which households increase the loan balance when they refinance. These data is available since 1999.

[1]FICO is the acronym for the credit score computed by the Fair Isaac Corporation.

In addition, we obtain aggregate time-series variables, including forecasts of unemployment, inflation and GDP from the Survey of Professional Forecasters. We obtain time-series of the Federal Funds Rate, house price and rental rates, and income per capita from the Federal Reserve Bank of St. Louis. Finally, we obtain measures of expected inflation from the Federal Reserve Bank of Cleveland.

Throughout, we confine our analysis to fixed-rate 30-year mortgages. Our results are robust to considering mortgages of different maturities. In our benchmark analysis, we end the sample in 2007. This decision is motivated by the widespread view that credit constraints were much more prevalent during the financial crisis period than in the preceding period (see e.g. Mian and Sufi (2014) and Beraja et al. (2018)).

4 Measuring the potential savings from refinancing

A key variable in our analysis is the potential savings that a household would realize by refinancing its mortgage at the current mortgage rate. Potential savings depend on a variety of factors, including the old and new mortgage interest rates, outstanding balances and the precise refinancing strategy that a household pursues. In general, it is impossible to construct a simple, non-parametric summary statistic of these potential savings. Our benchmark measure is the average interest-rate gap. This measure is based on the difference between the current and the alternative mortgage rate that the household i could refinance at.

We compute the average of time-t interest-rate gaps between new and old loan as:

$$A_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \left[r_{it}^{\text{old}} - r_{it}^{\text{new}} \right]. \tag{1}$$

Here, r_{it}^{new} is the interest rate at time t for a new 30-year conforming mortgage for the same FICO and region as the original mortgage. The new mortgage rate depends on borrower characteristics, including the same FICO and region. We group FICO scores into the following bins: below 600, $600-620$, $620-640$,... ,...,$760-780$, and greater

than 780. The variable n_t denotes the number of mortgages outstanding at time t. We refer to A_t as the average interest-rate gap. This gap is a real variable, since it is based on the difference between two nominal interest rates. The annualized unconditional quarterly mean and standard deviation of A_t are -14 basis points and 70 basis points, respectively. We condition on the household's region to take into account the possibility that mortgage rates vary by region, say because of differences in income or house price growth.[2]

The distribution of the interest rate gap varies considerably over time. To make this point concrete, Figure 1 displays the distribution of savings in 1997.Q4 and 2000.Q4. These dates correspond to local turning points in the real mortgage rate. The fraction of households with positive savings and the average savings are much higher in 1997.Q4 than in 2000.Q4.

We also considered versions of $r(.)_{it}^{\text{new}}$ that condition in a non-parametric way on additional variables such as the loan-to-valuation ratio or the mortgage balance. Adding these measures does not significantly improve the ability of $r(.)_{it}^{\text{new}}$ to fit of the cross-sectional variation of interest rates across new borrowers.

A virtue of our measure A_t is that it doesn't impose any assumptions about the household's refinancing decision. The downside is that it abstracts from relevant information such as outstanding balances or the characteristics of the new mortgage (e.g. duration and fixed versus variable interest rates).

In Appendix B3, we consider three alternative measures of the savings from refinancing. The first is the fraction of mortgages with a positive interest-rate gap. The second is based on the average present value of savings from pursuing a simple refinancing strategy. The third is based on the fraction of loans above a time-varying threshold for refinancing, defined in Agawal, Driscoll and Laibson (2013). Our results are robust

[2]As a practical matter, we find that our results are robust to not conditioning on the household's region. This finding is consistent with results in Hurst, Keys, Seru and Vavra (2016) who find little evidence of spatial variation in mortgage rates.

to using these alternative measures.

5 Empirical results

In this section, we study how the impact on refinancing activity of a change in the mortgage rate depends on our measure of the distribution of potential savings from refinancing. First, we establish some basic correlations estimated with ordinary least squares (OLS). Second, we implement an instrumental-variable (IV) strategy for measuring the marginal effect of a drop in mortgage rates on the fraction of loans that are refinanced. We show that this marginal effect is state dependent. Finally, we show that there is also state dependency in the impact of a fall in interest rates on economic activity.

5.1 State dependency and the efficacy of monetary policy

In this section, we investigate how the effect of monetary policy on refinancing activity depends on the state of the economy. We begin by considering the regression:

$$\rho^c_{t+4} = \beta_0 X^c + \beta_1 \Delta R^M_t + \beta_2 \Delta R^M_t \times A^c_{t-1} + \beta_3 A^c_{t-1} + \beta_4 Z_{t-1} + \beta_5 Z^c_{t-1} + \eta^c_t. \quad (2)$$

Here, ρ^c_{t+4} is the fraction of mortgages refinanced in county c between quarters t and $t+4$, X^c is a vector of county fixed effects, and ΔR^M_t denotes the percentage *fall* in our measure of the mortgage rate.[3] The variable A^c_{t-1} is the average interest-rate gap for mortgages in county c at time $t-1$. The vector Z_{t-1} denotes a set of time-varying controls. Motivated by results in Nakamura and Steinsson (2018), we include as controls the average forecast of the Survey of Professional Forecasters (SPF) for the following variables: real GDP growth (two year ahead), the civilian unemployment rate (two years ahead), and the CPI inflation rate (one and two years ahead). The variable

[3] If the mortgage rate falls by 25 basis points, $\Delta R_t = 0.25$. Defining ΔR_t as the fall in the interest rate, instead of the interest rate change makes the regression coefficients easier to interpret.

Z^c_{t-1} includes the following county-level controls: the unemployment rate, average log-change in real home equity, median age, share of employment in manufacturing, share of college educated and a Herfindahl index of the mortgage sector.[4] We include the latter index, developed in Scharfstein and Sunderam (2013), to capture any variation in pass through by region, induced by time variation in competition across counties. We cluster the standard errors at the county level.

The coefficient β_1 measures the effect of a change in mortgage rates when A^c_{t-1} is zero. The coefficient β_2 measures how the effect of an interest rate change depends on the level of A^c_{t-1}. Identification of β_1 and β_2 comes from both cross-sectional and time-series variation in the response of refinancing to interest rate changes.[5]

Table 1 reports our results. Column 1 reports results when regression (2) is estimated by OLS. Both β_1 and β_2 are statistically significant at least at a 5 percent significance level. While suggestive, it is hard to give a causal interpretation to these results because of potential endogeneity bias caused by any omitted variable that affects both mortgage rates and savings from refinancing. For example, suppose that during a recession more people are unemployed and therefore less willing to incur the fixed costs associated with refinancing. Also, suppose that the recession occurred because the Fed raised interest rates. Then, ΔR^M_t and $\Delta R^M_t \times A^c_{t-1}$ would be positively correlated with η^c_t creating a downward bias in β_1 and β_2.

To deal with the endogeneity problem, we estimate regression (2) using an IV strategy. We use two instruments for ΔR^M_t that exploit exogenous changes in monetary policy. The instruments are based on high-frequency movements in the Federal Funds futures rate and the two-year Treasury bond yield in a small window of time around

[4]Our results are robust to including as additional controls the fraction of mortages in county c that have adjustable rates and the interaction of this variable with the monetary policy shock.

[5]In practice, most of the variation in refinancing rates comes from time-series variation in interest rates. One way to see this result is to regress the rate of refinancing in county c at time t on time and county fixed effects. County fixed effects account for less than 20 percent of the variation in refinancing rates.

Federal Open Market Committee (FOMC) announcements.[6]

In the case of the Federal Funds futures, the monetary policy shock is defined as:

$$\epsilon_t = \frac{D}{D-t}\left(y_{t+\triangle^+} - y_{t-\triangle^-}\right). \tag{3}$$

Here, t is the time when the FOMC issues an announcement, $y_{t+\triangle^+}$ is the Federal Funds futures rate shortly after t, $y_{t-\triangle^-}$ is the Federal Funds futures rate just before t, and D is the number of days in the month. The $D/(D-t)$ term adjusts for the fact that Federal Funds futures contracts settle on the average effective overnight Federal Funds rate. We consider a 60-minute window around the announcement that starts $\triangle^- = 15$ minutes before the announcement. This narrow window makes it highly likely that the only relevant shock during that time period (if any) is the monetary policy shock. Following Cochrane and Piazessi (2002) and others, we aggregate the identified shock to construct a quarterly measure of the monetary policy shock. This aggregation relies on the assumption that shocks are orthogonal to economic variables in that quarter. The standard deviation of the implied monetary policy shock is 12 basis points.

In Appendix B1, we report our empirical analysis when we measure a monetary policy shock using the 2-year Treasury yield:

$$\epsilon_t = y^0_{t+\triangle^+} - y^0_{t-\triangle^-}.$$

Instrumental variable results. We begin by providing evidence that monetary-policy shocks are a strong instrument for changes in mortgage rates. First, we show that monetary policy shocks significantly affect mortgage rates. To this end, we estimate via OLS the contemporaneous change in the 30-year mortgage rate after a one percentage point monetary policy shock. Our point estimate is 60 basis points with a standard error of 25 basis points. Taking sampling uncertainty into account, our estimates are

[6]This approach has been used by Kuttner (2001), Gürkaynaka, Sack and Swanson (2005), Cochrane and Piazessi (2002), Nakamura and Steinsson (2018), Gorodnichenko and Weber (2015), and Wong (2017), among others.

consistent with those of Gertler and Karadi (2015), which range from 17 to 48 basis points.

Second, we estimate the following first-stage regressions:

$$\begin{aligned} \Delta R_t^M &= \alpha_0 + \alpha_1 \varepsilon_t + \alpha_2 \varepsilon_t \times A_{t-1}^c + \eta_{1t}, \\ \Delta R_t^M A_{t-1}^c &= \gamma_0 + \gamma_1 \varepsilon_t + \gamma_2 \varepsilon_t \times A_{t-1}^c + \eta_{2t}. \end{aligned}$$

Table 2 reports our results. The F test for the joint significance of the regression coefficients is greater than ten. This result is consistent with the notion that policy shocks are strong instruments.

We report our regression results in column 2 of Table 1. We cluster the standard errors at the county level. The estimated values of β_1 and β_2 are statistically significant at the one percent significance level. Notice that the IV estimate of β_2 is substantially larger than the OLS estimate. This result is consistent with the discussion above of the downward bias in the OLS estimate.

To interpret these coefficients, suppose that all the independent variables in regression (2) are initially equal to their time-series averages and that the average interest-gap is initially equal to its mean value of -14 basis points. The unconditional average share of loans that are refinanced is 7.9 percent. The estimates in column 2 of Table 1 imply that a 25 basis points drop in mortgage rates raises the share of loans that are refinanced to 8.6 percent.[7] Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of -14 basis points plus one standard deviation 70 basis points. Then, a 25 basis points drop in mortgage rates raises the share of loans that are refinanced to 13.2 percent.[8] So, the marginal impact of a one standard-deviation increase in the average interest-rate gap is 4.7 percent. This effect is large relative to the average annual refinancing rate, 7.9 percent.

[7]This value is given by $7.9\% + 0.25 \times (\beta_1 + \beta_2 \times -0.14) = 8.6\%$.
[8]This value is given by $7.9\% + 0.25 \times (\beta_1 + \beta_2 \times 0.56) = 13.2\%$.

As a robustness test we also included in regression (2) interaction terms of the form $\Delta R_t^m Z_{t-1}^c$. These results are reported in Table B2. The implied estimates of β_2 are statistically indistinguishable from those reported in column 2 of Table 1. The fact that including the interaction terms does not change the estimated elasticities implies that the state dependency that we highlight is distinct from other potential mechanisms explored in the literature. These mechanisms include, for instance, differential responses in refinancing to a decline in mortgage rates due to differences in competitiveness of the local lending market. It is also distinct from state dependency related to cross-county variation in the value of home equity.

5.2 Cash-out refinancing

In this subsection, we use Freddie Mac's data on single-family loans to study how cash-out refinancing responds to changes in mortgage rates. Cash-out refinancing occurs when the balance of the new mortgage is higher than that of the old mortgage. We know from Mian and Sufi (2011) that households predominantly use this type refinancing to increase their consumption. So, cash-out refinancing plays an important role in the determining the effects of changes in interest rates on consumption.

We run a version of regression (2) in which the dependent variable is the fraction of total loans with cash-out refinancing in county c between quarters t and $t+4$. Panel A of Table 3 reports our results. Both β_1 and β_2 are significant at the one-percent significance level. To interpret these coefficients, suppose that all independent variables in regression (2) are initially equal to their time-series averages and that the average interest-gap is initially equal to its mean value of -14 basis points. The estimates in column 2 of Panel A of Table 3 imply that a 25 basis points drop in mortgage rates raises the share of loans with cash-out refinancing by 1.2 percent. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of -14 basis points plus one standard deviation 70 basis points. Then, a 25 basis points drop in mortgage rates raises the share of loans

with cash-out refinancing by 4.3 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 3.1 percent. This effect is large relative to the average annual cash-out refinancing rate, 5.5 percent.

We also estimate a version of regression (2) in which the dependent variable is the log change in the balance of the mortgages with cash-out refinancing. Panel B of Table 3 reports our results. Both β_1 and β_2 are significant at the one percent significance level. To interpret these coefficients, suppose that all independent variables in regression (2) are initially equal to their time-series averages and that the average interest-gap is initially equal to its mean value of -14 basis points. The estimates in column 2 of Panel B of Table 3 imply that a 25 basis points drop in mortgage rates raises the balance of the mortgages with cash-out refinancing by 5.2 percent. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of -14 basis points plus one standard deviation 70 basis points. Then, a 25 basis points drop in mortgage rates raises the balance of the mortgages with cash-out refinancing by 8.9 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 3.8 percent. The median mortgage balance in 2007 was roughly $\$123,000$. So, an increase in mortgage balance of 3.8 percent translates into equity extraction of roughly $\$4,700$, a substantial amount of cash that becomes available for consumption.

5.3 Refinancing and economic activity

We now study how a change in mortgage rates affects economic activity. In our analysis, we study county-level unemployment rates. We also consider monthly data on the number of permits required for new privately-owned residential buildings from the Census Building Permits Survey, aggregated to quarterly frequency. This series, which starts in 2000, is of particular interest to us because it is the only component of the Conference Board's leading indicator index available at the county level.

To be clear, we are not the first to establish that changes in mortgage rates induced

by monetary policy shocks affect economic activity. We are simply establishing that these effects are state dependent.

We begin by considering a regression where the dependent variable is the change in the unemployment rate between quarter t and $t+4$:

$$\Delta \text{Unemployment}_{t,t+4} = \theta_0 X^c + \theta_1 \Delta R_t^M + \theta_2 \Delta R_t^M \times A_{t-1}^c + \theta_3 A_{t-1}^c + \eta_t^c. \qquad (4)$$

Table 4, column II reports our IV estimates. Standard errors are clustered at the county level. The point estimate of θ_1 is statistically significant at a 10 percent level while θ_2 is statistically significant at the 1 percent level. To interpret the point estimates suppose that all independent variables in regression (5) are initially equal to their time-series averages. Our estimates imply that a 25 basis points drop in mortgage rates lowers the unemployment rate by 0.6 percent. Suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of (-14 basis points) plus one standard deviation (70 basis points). Then a 25 basis points drop in mortgage rates lowers the unemployment rate by 1.8 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 1.2.

We now consider a version of the regression where the dependent variable is the annual log-change in new building permits:

$$\Delta \log \text{ Permits}_{t,t+4} = \theta_0 X^c + \theta_1 \Delta R_t^M + \theta_2 \Delta R_t^M \times A_{t-1}^c + \theta_3 A_{t-1}^c + \eta_t^c. \qquad (5)$$

Table 4, column II reports our IV estimates. Both θ_1 and θ_2 are statistically significant at least at a 5 percent significance level. To interpret the point estimates suppose that all independent variables in regression (5) are initially equal to their time-series averages. The estimates in column 2 imply that a 25 basis points drop in mortgage rates raises the percentage change in new permits to 17.0. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of (-14 basis points) plus one standard deviation (70 basis

points). Then a 25 basis points drop in mortgage rates raises the percentage change in new permits to 23.6 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 6.6. This effect is large relative to a one standard deviation change in housing permits, which is 26 percent.

Overall, we view the results of this section as providing strong support for two hypotheses. First, the effect of a change in the interest rate on refinancing activity is state dependent. When measures of the average gains from refinancing are high, a given fall in interest rate induces a larger rise in refinancing activity. Second, the effect of a change in the interest rate on economic activity, as measured by new housing permits or the rate of unemployment, is state dependent in a similar way. This finding is consistent with the results in Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017). These authors show that households who experience a drop in monthly mortgage payments increase their car purchases. It is also consistent with results in Berger, Milibrandt, Tourre and Vavra (2018) who show that there is a state-dependent rise in auto registrations when interest rates fall.

6 A life-cycle model

To analyze the state-dependent effects of monetary policy, we use a life-cycle model with incomplete markets, short-term borrowing constraints, refinancing costs, and loan-to-value constraints on mortgages. Our model extends the model in Wong (2018) to allow for state dependency in the aggregate state processes (such as interest rates, income, house prices and rental rates). This extension allows to incorporate state-dependent feedback effects of monetary policy shocks on aggregate variables.

We use the model for four purposes. First, we quantify the structural factors that drive the state-dependent effects of monetary policy. Second, we estimate the state-dependent effect of an exogenous change in the interest rate on consumption. Third, we study how the potency of monetary policy is affected by a long period of low interest

rates. Finally, we analyze the impact of the observed long-term decline in refinancing costs on the efficacy and state dependency of monetary policy.

It is evident that there is a great deal of heterogeneity across households in their propensity to refinance in response to an interest rate cut. One way to capture that heterogeneity is to allow for a great deal of heterogeneity in unobserved fixed costs of refinancing. An alternative is to model that heterogeneity in refinancing behavior as reflecting demographics, initial asset holdings and idiosyncratic income shocks. We choose the second strategy to minimize the role of unobservable heterogeneity. An advantage of this approach is that it is consistent with the positive correlation between consumption growth and refinancing decisions at the household level. This correlation is important for generating a response of aggregate consumption to interest rate changes.[9]

Households. The economy is populated by a continuum of people indexed by j. We think of the first period of life as corresponding to 25 years of age. Each person can live up to 60 years. The probability of dying at age a is given by $1 - \pi_a$. Conditional on surviving, people work for 40 years and retire for 20 years. People die with probability one at age $T = 85$.

The momentary utility of person j at age a and time t is given by:

$$u_{jat} = \frac{\left(c_{jat}^{\alpha} h_{jat}^{1-\alpha}\right)^{1-\sigma} - 1}{1-\sigma}, \, \sigma > 0.$$

Here, c_{jat} and h_{jat} denote the consumption and housing services of person j with age a, respectively. Agents derive housing services from either renting or owning a house. Renters can freely adjust the stock of rental housing in each period. Homeowners pay a lump-sum transaction cost F when they enter a new mortgage or refinance an existing mortgage. The stock of housing depreciates at rate δ.

[9]Recent work that emphasizes the correlation between household consumption and interest rate changes for understanding the behavior of aggregate consumption includes Auclert (2018), Kaplan, Violante and Moll (2018), and Wong (2018).

Upon death, the wealth of person j with age a, W_{jat}, is passed on as a bequest.[10] Person j derives utility $B\left(W_{jat}^{1-\sigma}-1\right)/\left(1-\sigma\right)$ from a bequest. Here B is a positive scalar.

Income processes. The time-t labor income of person j at age a, y_{jat}, is given by:

$$\log(y_{jat}) = \chi_a + \eta_{jt} + \phi_a \log(Y_t). \tag{6}$$

Here χ_a and η_{jt} are a deterministic age-dependent component and a stochastic, idiosyncratic component of y_{jat}, respectively. We assume that

$$\eta_{jt} = \rho_\eta \eta_{jt-1} + \varepsilon_{\eta t},$$

where $|\rho_\eta| < 1$ and $\varepsilon_{\eta t}$ is a white noise process with the standard error, σ_η. The variable Y_t denotes aggregate real income. The term ϕ_a captures the age-specific sensitivity of y_{jat} to changes in aggregate real income.

As in Guvenen and Smith (2014), we assume that a person receives retirement income that consists of a government transfer. The magnitude of this transfer is a function of the labor income earned in the year before retirement.

Mortgages. Home purchases are financed with fixed rate mortgages. An individual j who enters a mortgage loan at age a in date τ, pays a fixed interest rate $R_{ja\tau}$ and makes a constant payment $M_{ja\tau}$. The mortgage principal evolves according to:

$$b_{j,a+1,t+1} = b_{jat}(1 + R_{ja\tau}) - M_{ja\tau}.$$

Mortgages are amortized over the remaining life of the individual. So, the maturity of a new loan for an a-year old person is $m(a) = T - a$. The fixed interest rate $R_{ja\tau}$ is equal to $r_\tau^{m(a)}$, which is the time-τ market interest rate for a mortgage with maturity $m(a)$.

[10] If the agent has an outstanding mortgage upon death, the house is sold to pay the mortgage and the remainder of the estate is passed on as a bequest.

The mortgage payment, $M_{ja\tau}$, is given by:

$$M_{ja\tau} = \frac{b_{ja\tau}}{\sum_{k=1}^{m(a)}(1+R_{ja\tau})^{-k}}. \tag{7}$$

If a person refinances at time t, the new mortgage rate is given by the current fixed mortgage rate:

$$R_{jat} = r_{\tau}^{m(a)}.$$

Bond holdings. A person can save by investing in a one-year bond that yields an interest rate of r_t. The variable s_{jat} denotes the time-t bond holdings of person j who is a years old. Bond holdings have to be non-negative, $s_{jat} \geq 0$.

Loan-to-value constraint. At the time of origination, the size of a mortgage loan must satisfy the constraint:

$$b_{jat} \leq (1-\phi)p_t h_{jat}.$$

Here, p_t is the time-t price of a unit of housing and $\phi p_t h_{jat}$ is the minimum down payment on a house.

State variables. The state variables are given by $z = \{a, \eta, K, S\}$. Here, a, η, and K denote age, idiosyncratic labor income, and asset holdings, respectively. The vector K includes short-term asset holdings (s), the housing stock (h^{own} for homeowners, zero for renters), the mortgage balance (b for homeowners, zero for renters), and the interest rate (R) on an existing mortgage. Finally, S denotes the aggregate state of the economy which consists of the logarithm of real output, y_t, the logarithm of real housing prices, p, the real interest rate on short-term assets, r, and the logarithm of economy-wide average positive savings from refinancing, A. We assume that S_t is a stationary stochastic process (see Section 6.2).

Mortgage interest rate and rental rates. It is difficult for traditional asset pricing models to account for the empirical properties of mortgage interest rates, rental rates and housing prices (see Piazzesi and Schneider (2016)). For this reason, we assume that these variables depend on the aggregate state of the economy via functions that we estimate. This approach allows the model to be consistent with the empirical properties of these variables.

The interest rate of a mortgage, r_t^m, is given by

$$r_t^m = a_0^m + a_1^m r_t + a_2^m y_t. \tag{8}$$

This formulation captures, in a reduced-form way, both the term-premia and changes in risk-premia that arise from shocks to the aggregate state of the economy.

The rental rate is given by:

$$\log(p_t^r) = \alpha_0 + \alpha_1 r_t + \alpha_2 y_t + \alpha_3 p_t. \tag{9}$$

Value functions. We write maximization problems in a recursive form. To simplify notation, we suppress the dependence of variables on j and t. We denote by $V(z)^{\text{rent}}$, $V(z)^{\text{own \& no-adjust}}$, and $V(z)^{\text{own \& adjust}}$ the value functions associated with renting, owning a home and not refinancing, and owning a home and refinancing, respectively. A person's overall value function, $V(z)$, is the maximum of these value functions:

$$V(z) = \max\left\{V(z)^{\text{rent}}, V(z)^{\text{own \& no-adjust}}, V(z)^{\text{own \& adjust}}\right\}. \tag{10}$$

A renter maximizes

$$V(z)^{\text{rent}} = \max_{c, h^{\text{rent}}, s'} u\left(c, h^{\text{rent}}\right) + \beta E\left[V(z')\right], \tag{11}$$

subject to the budget constraint,

$$c + s' + p^r h^{\text{rent}} = y + (1-\delta)ph^{\text{own}} + (1+r)s - b(1+R), \tag{12}$$

and the borrowing constraint on short-term assets,

$$s' \geq 0.$$

The discount rate is denoted by β. The terms $(1-\delta)ph^{\text{own}}$ and $b(1+R)$ in equation (12) take into account the possibility that the renter used to be a home owner. The renter's housing stock and mortgage debt are both zero:

$$h'^{\text{own}} = b' = 0.$$

A homeowner who does not refinance his mortgage maximizes:

$$V(z)^{\text{own \& no-adjust}} = \max_{c,s'} u\left(c, h^{\text{own}}(1-\delta)\right) + \beta E\left[V(z')\right], \tag{13}$$

subject to the budget constraint,

$$c + s' = y + (1+r)s - M,$$

the law of motion for the mortgage principal

$$b' = b(1+R) - M,$$

and the short term borrowing constraint

$$s' \geq 0.$$

Since the person doesn't refinance, the interest rate on his mortgage remains constant

$$R' = R.$$

The mortgage payment is given by equation (7).

A homeowner who refinances, maximizes:

$$V(z)^{\text{own \& adjust}} = \max_{c,s',h'^{\text{own}},b'} u\left(c, h'^{\text{own}}\right) + \beta E\left[V(z')\right],$$

subject to the budget constraint

$$c + s' + ph'^{\text{own}} - b' + F = y + (1-\delta)ph^{\text{own}} + (1+r)s - b(1+R),$$

the borrowing constraint on short term assets,

$$s' \geq 0,$$

and the minimal down payment required on the mortgage,

$$b' \leq (1-\phi)ph'^{\text{own}}.$$

The new mortgage interest rate is given by:

$$R' = r^m.$$

The problem for a retired person is identical to that of a non-retired person, except that social security benefits replace labor earnings.

6.1 Calibration

Our parameter values are summarized in Table 5. We adopt a standard value for σ and choose B, β, and α to target key moments of the savings and asset-holding profiles. These moments include the average home ownership rate, the liquid wealth-to-income ratio for working age households, and the share of wealth held by older households (aged 65+) from the 2007 Survey of Consumer Finances. The idiosyncratic-income parameters ρ_η and σ_η are chosen to match the annual persistence and standard deviation of residual earnings in the Panel Study of Income Dynamics. The deterministic, age-specific vector χ_a is chosen to match average log earnings by age estimated by Guvenen et al. (2015). We choose ϕ_a to match the correlation between real aggregate income per capita and age-specific earnings in the Current Population Survey. The house depreciation rate, δ, is chosen to be consistent with the average ratio of residential investment to the residential stock from the Bureau of Economic Analysis. We set ϕ so that, in line with

Landvoigt, Piazzesi and Schneider (2015), the minimum mortgage downpayment is 20 percent. We estimate the parameters of the processes for mortgage rates (a_0^m,a_1^m, and a_2^m in equation (8)) and and rental rates (α_0, α_1, α_2, and α_3 in equation (9)). We discuss the fit of these processes to the data below. Finally, we choose the fixed cost, F, to be equal to $\$2,100$ (2 percent of median house price) to match the average quarterly fraction of new loans of 4.5 percent.[11] Recall that we think of the first period of life as 25 years of age. Age-dependent survival probabilities are given by the U.S. actuarial life-expectancy tables and assume a maximum age of 85. Assets and income in the first period are calibrated to match average assets and income for persons of ages 20 to 29 in the 2004 Survey of Consumer Finances.

6.2 The evolution of the aggregate states

To solve their decision problem, people must form expectations about their future income, mortgage rates, house prices, and rental rates. Because of its partial equilibrium nature, our model does not imply a reduced-form representation for these variables. It seems natural to assume that people use a time-series model for these variables that has good forecasting properties.

Recall that we model the mortgage rate with maturity m as a function of r_t and y_t (see equation (8)). We estimate this function using OLS. Table 6 reports our estimates. Figure 2 shows that the estimated version of equation (8) does a very good job at accounting for the time-series behavior of the 30-year mortgage rate over the period 1989-2008.

We also model the rental rate as a linear function of r_t, y_t and p_t (see equation (9)). We estimate this function using the national house price and rent indices obtained from the Federal Reserve Bank Dallas. Figure 3 shows that the estimated version of equation (9) does a very good job at accounting for the time-series behavior of the logarithm of

[11] See DeFusco and Mondragon (2018) for evidence that fixed costs, including closing costs and refinancing fees, are an important determinant of refinancing decisions.

the house price-to-rent ratio over the period $1989 - 2008$.

We estimated a suite of quarterly time-series models for the aggregate state vector S_t. Recall that S_t consists of $\log(r_t)$, $\log(y_t)$, $\log(p_t)$, and $\log(A_t)$. We eliminated from consideration models with explosive dynamics. We judged the remaining models balancing parsimony and the implied average (over time and across variables) root-mean-square-error (RMSE) of one-year-ahead forecasts. Parsimony is important for the computational tractability of our structural model.

We settled on the following model for quarterly changes in S_t:

$$\Delta S_t = B_0 + B_1 \Delta S_{t-1} + B_2 \Delta \log(r_{t-1}) a_{t-1} + u_t. \tag{14}$$

Here, B_1 is a 4×4 matrix, B_0 and B_2 are 4×1 vectors, and u_t is a Gaussian disturbance. The variable a_{t-1} is the logarithm of economy-wide average positive savings from refinancing at time $t-1$, $\log(A_{t-1})$.

Appendix C reports the average RMSE for the alternative models that we considered. These models include specifications with up to two lags of ΔS_t and $\Delta \log(r_{t-1}) a_{t-1}$. In addition, we included cross products of all the variables in different combinations as well as squares and cubes of the different variables. We also considered different moments of different measures of the gains from refinancing. For example, we replace a_t with average savings (in levels), median savings, average interest-rate gap, logarithm of average positive interest-rate gap, median of the interest-rate gap, fraction of mortgages with positive savings, and standard deviation of savings. To conserve on space we do not report these results.

None of the RMSE associated with the alternative specifications was smaller, taking sampling uncertainty into account than the RMSE associated with specification (14). At the same time, specification (14) did have a statistically significant smaller RMSE than many of the alternatives.

Table 7 reports point estimates and standard errors for B_1 and B_2 associated with specification (14). The coefficients in B_2 are statistically significant at the one percent

level for $\log(r_t)$ and $\log(p_t)$ and at the 10 percent level for a_t.

A natural question is whether the inclusion of a_t and $\Delta r_{t-1}a_{t-1}$ in specification (14) helps reduce the RMSE for the three aggregate variables ($\log(r_t)$, $\log(y_t)$, $\log(p_t)$) that people need to forecast to solve their problem. Simply adding a_t to a linear VAR for $\log(r_t)$, $\log(y_t)$, $\log(p_t)$, reduces the average RMSE for $\log(r_t)$, $\log(y_t)$, $\log(p_t)$ in a modest but statistically significant way (from 0.0298 to 0.0258). Adding the interaction term $\Delta r_{t-1}a_{t-1}$ results in an even more modest, but statistically significant reduction, in the average RMSE for $\log(r_t)$, $\log(y_t)$, $\log(p_t)$.

We compute the impulse response to a monetary policy shock implied by (14) as follows. First, the shocks u_t are regressed on the monetary-policy shock. Second, we compute the impact of a monetary-policy shock on $\log(r_t)$, $\log(y_t)$, $\log(p_t)$, and $\log(A_t)$. Figure 4 displays the associated impulse response functions for a one-standard-deviation shock to monetary policy. We see than an expansionary monetary policy shocks is associated with a persistent rise in income and house prices as well as a decrease in average positive savings from refinancing.

Recall that our model abstracts from growth. To solve the model, we set the constant vector, B_0, in (14) to zero and work with the implied VAR for the level of the variables.[12] We approximate this VAR with a Markov chain using the procedure described in Appendix D. A key property of the Markov chain is that the implied impulse response functions to a monetary policy shocks are stationary.

7 Empirical performance of the model

We now compare our model with the data along a variety of dimensions. Model statistics are computed using simulated data generated as follows. We start the simulation in 1994, assuming that people have the distribution of assets, liabilities and mortgage rates observed in the data. We feed into the model the realized values of $\log(r_t)$, $\log(y_t)$, and

[12]This procedure is equivalent to estimating the VAR using data that have been demeaned.

$\log(p_t)$ for the period 1995-2007. We simulate the idiosyncratic component of income, y_{jat}, for each household in our model.

7.1 Life-cycle dynamics.

Consider first the model's ability to account for how the behavior of U.S. households evolves with age. Figure 5 displays home-ownership rates, as well as the logarithm of non-durable consumption, the ratio of debt to net wealth, and household net wealth. The model does a reasonably good job of accounting for these moments of the data. It implies that home ownership rates rise with age and stabilize when people reach their 40s.

To understand the mechanisms that underlie Figure 5, it is useful to consider a simplified analysis of the cost of owning versus renting.[13] The net benefit of owning a home is given by:

$$\frac{p_t^r}{p_t} + E_t \frac{p_{t+1} - p_t}{p_t} - r_t \left(1 - \frac{b_t}{p_t}\right) - \frac{b_t}{p_t} r_t^m - \delta - r_t \frac{F}{p_t}. \tag{15}$$

The first term in equation (15) is the savings from not paying rent, which we express as a fraction of the house price, p_t^r/p_t. In our sample, p_t^r/p_t is on average 7.7 percent. The second term in this expression is the expected real rate of housing appreciation. In our calibration, $E_t\left(p_{t+1} - p_t\right)/p_t$ is on average one percent per year. The third term is the opportunity cost of the down payment, $1 - b_t/p_t$ on a house. The fourth term is the mortgage payment on the house, where r_t^m denotes the average mortgage rate. We estimate that the average value of r_t and r_t^m in our sample is 3.5 percent and 6.5 percent, respectively. The fifth term, δ, is the rate of depreciation of the housing stock. We assume that δ is three percent per annum. The last term in equation (15) is the fixed cost of buying a house as a percentage of the house price. Recall that we assume $F = \$2,100$ which represents roughly one percent of the average price of a house in our

[13] See Díaz and Luengo-Prado (2012) for a review of the literature on the user cost of owning a home.

sample ($189,000).[14]

A number of observations follow from equation (15). First, other things equal, the higher is the rental-price ratio and the expected real rate of housing appreciation, the more attractive it is to own rather than rent a house. Second, other things equal, the less expensive is the house (i.e. the lower is p_t) the larger is the negative impact of a fixed cost on the desirability of purchasing a home ($r_t F/p_t$). Third, other things equal, the higher the down payment a household can make, the more attractive it is to own a home. To see this effect, it is convenient to rewrite the sum of the opportunity cost of the down payment and the mortgage payment, $r_t\left(1-b_t/p_t\right)+\left(b_t/p_t\right)r_t^m$ as:

$$r_t+\frac{b_t}{p_t}\left(r_t^m-r_t\right). \tag{16}$$

The first term (r_t), is the opportunity cost of purchasing a home without a mortgage. The second term, is the additional interest costs associated with buying a home with a mortgage of size b, which requires paying the spread ($r_t^m - r_t$). From the second term, it is clear that, other things equal, the bigger is the mortgage the less desirable it is to buy a home.

With these observations as background, consider again Figure 5. The model implies that home ownership rates rise as people get older. This result follows the fact that, on average, income rises as a person ages, peaking between 45 and 55 years of age. As income rises, people want to live in bigger homes, which reduces the impact of fixed costs on the desirability of purchasing a home ($r_t F/p_t$). Also, as income rises, people can afford bigger down payments on those homes, which, as we just discussed, reduces the user cost of owning a home. Taken together, both forces imply that home ownership should on average rise until people are 55. Thereafter, home ownership rates roughly stabilize. However, many elderly homeowners downsize. They sell their old homes and use the proceeds to buy smaller homes which they eventually leave as bequests.

[14]One difference between renting and buying not captured by equation (15) is that renters can freely vary the amount of housing services they purchase while home owners have to pay a fixed cost to change the size of their house.

From Figure 5, we also see that household debt declines with age. This fact reflects two forces. First, people pay down their mortgages over time reducing their debt. Second, elderly people who are downsizing have small mortgages. Finally, household net wealth rises on average with age, as people pay off their mortgages and save for bequests.

Figure 5 also shows that non-durable consumption rises until people reach ages 45 to 55 and then falls. The rise results from two forces. First, people face borrowing constraints which prevent them from borrowing against future earnings. Second, most households have an incentive to save so they can make a down payment on their mortgage. The fall in non-durable consumption after age 55 reflects the presence of a bequest motive. As people age, the weight of expected utility from leaving bequests rises relative to the weight of utility from current consumption. When we reduce B, the parameter that controls the strength of the bequest motive, consumption becomes smoother.

7.2 Refinancing and the interest-rate gap

In the data, the average annual refinancing rate is 7.9 percent with a standard deviation of 4 percent. In the model, the average annual refinancing rate is 7.5. So, taking sampling uncertainty into account, the model does a good job at accounting for the average refinancing rate. The model is also consistent with the fraction of new mortgages issued in each period. This fraction is 25 percent both in the model and the data.

Figure 6 plots the fraction of loans that are refinanced as a function of the interest-rate gap faced by people in the economy. We display these statistics both for the data and the model. The data-based statistics are computed as follows. We bin all the loans according to the interest-rate gap ranges indicated in the figure. For every bin, we calculate the fraction of loans that were refinanced. Figure 6 displays these fractions and the corresponding 95 percent confidence intervals.

The model-based statistics are computed as follows. The initial distribution of age,

assets, mortgage debt and mortgage rates is the same as the actual distribution in 1994. We assume there are $100,000$ households in the model economy and draw idiosyncratic shocks for each of these people. At each point in time, we feed in the actual values of the aggregate state of the economy from 1995 to 2007 for r_t, y_t, and p_t. We use the model to construct the time series for a_t, the logarithm of economy-wide average positive savings from refinancing. People use this variable to form expectations for future aggregate states using equation (14). At every point in time, from 1995 to 2007, the model generates a distribution of interest-rate gaps and refinancing decisions. So we are able to compute the same moments that we estimated from the data. As can be seen from Figure 6, taking sampling uncertainty into account the model does well at accounting for the data.[15]

7.3 State dependency of refinancing decisions

We now consider whether the model is capable of accounting for the state-dependent nature of the effects of monetary policy on refinancing decisions that we document in our empirical work. We use the simulated data to estimate the following regression:

$$\rho_{t+4} = \beta_0 + \beta_1 \Delta R_t^M + \beta_2 \Delta R_t^M \times A_{j,t-1} + \beta_3 A_{j,t-1} + \eta_t. \tag{17}$$

Regression (17) is a version of regression (2) without county fixed effects. We estimate regression (17) using the monetary policy shock as instruments. Table 8, panel A reports the model-based and data-based estimates of β_1 and β_2. The data estimates are reproduced from column 2 of Table 1. From Table 8, panel A we see that the model does quite well at accounting for the regression results. Taking sampling uncertainty into account, the model- and data-based estimates are not significantly different from each other.

[15]See Andersen, Campbell, Nielsen, and Ramadorai (2015) and the references therein for evidence that some agents do not refinance their fixed-rate mortgage when market rates fall below their locked-in mortgage rate.

7.4 State dependency of mortgages for new home purchases

It is of interest to ask whether the model accounts for the response of purchases of new homes to an exogenous change in mortgage rates. To this end, we first run a version of regression (2) where the left-hand side is the fraction of new mortgages used to purchase a new home relative to the number of outstanding mortgages. Table 8, panel C reports our results. Notice that both regression coefficients are statistically significant at the one percent level and that there is strong evidence of state dependency in the response of new home purchases to changes in mortgage rates.

To interpret these coefficients, suppose that all the independent variables in the regression are initially equal to their time-series averages and that the average interest-gap is initially equal to its mean value of -14 basis points. The estimates in column 1 of Panel C of Table 8 imply that a 25 basis points drop in mortgage rates raises the fraction of loans for new purchases by 3.5 percent. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of -14 basis points plus one standard deviation 70 basis points. Then, a 25 basis points drop in mortgage rates raises the fraction of loans for new purchases to 6.10 percent. So, the marginal impact of a one standard-deviation increase in the average interest-rate gap is 2.6 percent.

Column 2 of Table 8, panel C shows that the regression coefficients implied by our model are consistent with the empirical patterns discussed above. However, the model somewhat understates the direct impact of a change in mortgage rates and overstates the state dependency of new home purchases.

8 Model implications

In this section, we use our model to study the state-dependent effects of a fall in interest rates on consumption and how the potency of monetary policy depends on the past behavior of interest rates.

8.1 State-dependent effects of a fall in interest rates on consumption

We now use simulated data to estimate the effect of an exogenous change in the interest rate on the annual change in the logarithm of consumption for household j (c_{jt}):

$$c_{jt+1} - c_{jt} = \beta_{j0} + \beta_1 \Delta R_t^M + \beta_2 \Delta R_t^M \times A_{t-1} + \beta_3 A_{t-1} + \eta_t^c. \tag{18}$$

The coefficients in this regression are estimated using the monetary shocks as instruments. Table 11 shows the effect of a 50 basis points fall in interest rates. The total effect on consumption of an exogenous change in mortgage rates is 2.06 percent. The direct effect ($\beta_1 \Delta R_t^M$) is 1.21 percent. The state dependent effect ($\beta_2 \Delta R_t^M \times$ average interest-rate gap) is 0.85 percent.[16]

To understand the mechanisms that underlie these effects, we estimate regression (18) for two separate groups: households that have positive liquid assets ($s_{jt} > 0$) and households that do not have positive liquid assets ($s_{jt} \leq 0$). We call the first group of households unconstrained and the second group constrained. A fraction 40 percent of total households is, on average, constrained in our model. This fraction is consistent with the results in Kaplan, Violante and Weidner (2014). More than 80 percent of the constrained households are home owners. These households correspond to what Kaplan, Violante and Weidner (2014) call wealthy hand-to-mouth consumers. The total effect on consumption of an exogenous change in mortgage rates is 4 and 0.63 percent for constrained and unconstrained households, respectively. So, the consumption response is predominantly driven by the constrained households. We obtain similar results when we define constrained (unconstrained) households as having less (more) liquid assets than two weeks of income.

Roughly 80 percent of the households who refinance engage in cash-out refinancing,

[16] Very little of the consumption response to mortgage rate changes is driven by the associated changes in house prices. We established this result by computing the response of consumption to a change in mortgage rates keeping house prices constant. The implied consumption response is similar to that obtained when we do allow house prices to change.

that is, the size of their new mortgage is larger than the balance of the old mortgage. This value is in line with the evidence presented by Chen, Michaux, and Roussanov (2013). Using a conservative estimate based on conforming mortgages, these authors argue that over the period 1993-2010 on average about 70 percent of refinanced loans involve cash-out.

In response to a one-percent decline in mortgage rates, households who engage in cash-out refinancing in our model increase their loan balances by 27.7 percent. This effect is broadly consistent with the empirical estimates of Bhutta and Keys (2016).[17]

To assess the model's implications for the state-dependent nature of cash-out refinancing, we use simulated data and estimate a version of regression (17). Here, the dependent variable is the fraction of total loans with cash-out refinancing. Our results are reported in Table 8, panel C. Comparing columns I and II, we see that in the data the state dependent effect of an interest rate cut on refinancing and cash-out refinancing are about the same. The model captures, qualitatively, the state-dependent nature of cash-out refinancing, i.e. the larger are potential savings the more cash our refinancing responds to an interest rate cut.

In our model, we abstract from the effects of refinancing decisions on bank owners. If those owners are constrained and the profits of the bank rise or fall one to one by the amount that consumers save by refinancing, the refinancing channel has no aggregate effect on consumption. However, it is natural to assume that bank owners behave like unconstrained households. Under this assumption, the negative effect of refinancing on the consumption of bank owners is much smaller in absolute value than the positive effect on the consumption of constrained households.[18] As a result, the overall effect of refinancing on aggregate consumption is positive. To explore the potential size of this effect we do a simple back-of-the-envelope calculation. We compute the change

[17]Using Equifax data, these authors estimate that, in response to a one-percent decline in mortgage rates, households who engage in cash-out refinancing increase their loan balances by 22.7 percent.

[18]The negative effect on U.S. consumption of the decline in profits due to refinancing is mitigated by the fact that some of stock shares of U.S. banks are owned by foreigners.

in consumption implied by a permanent-income-style calculation by multiplying the present value of total savings from refinancing by the steady-state risk-free rate (3.5 percent). We subtract this value from total consumption. This adjustment has a negligible impact with the growth rate of consumption falling by less than 0.01 percent.

8.2 State dependency and the potency of monetary policy

In this subsection, we provide intuition for the state-dependent effects of monetary policy in our model by comparing the impact of a given interest rate cut in different scenarios. We then use our model to quantify an important cost of prolonged low-interest rate periods. Finally, we consider the impact of a secular decline in refinancing costs.

8.2.1 Model experiments

In all of the experiments considered in the subsection the model economy starts in steady state, i.e. the aggregate state variables have been constant and equal to their unconditional means. However, people have been experiencing ongoing idiosyncratic shocks to their income.

The three paths that we consider are displayed in Figure 7. At each point in time, people form expectations about aggregate states according to the Markov-chain approximation to the demeaned level representation of the aggregate states associated with (14). Our results are summarized in panel A of Table 9.

In the first scenario, we consider the effect of an interest rate cut when the economy starts in steady state and remains there until period of six. At time seven, we feed an interest-rate shock into the model that generates a 50-basis point fall in the interest rate. We refer to this scenario as the benchmark scenario. From row (i) of Table 9, panel A we see that 26 percent of people refinance in the impact period of the shock and aggregate consumption increases 1.3 percent. There are two reasons why these effects are so large. First, all existing homeowners with a mortgage have a positive rate gap

after the interest rate cut because they obtained their mortgages at the steady-state mortgage interest rate. Second, people expect the interest rate to revert to the mean, so period seven is a good time to refinance.

In the second scenario, the central bank steadily raises interest rates starting in period one until they peak in period six. The central bank then cuts the interest rate by 50 basis points in period seven. From row (ii) of Table 9, panel A we see that only 16 percent of households refinance in the impact period of the shock and there is only a 0.1 percent rise in consumption. The reason for these small effects is that only 5 percent of people face a positive interest-rate gap in period six. These are the people who entered new mortgages despite rising interest rates due to life-cycle considerations or idiosyncratic income shocks.

In the third scenario, the central bank steadily lowers interest rates starting in period one until they trough in period six. The central bank then cuts interest rates by 50 basis points in period seven. From row (ii) of Table 9, panel B we see that in this scenario, 23 percent of people refinance in the impact period of the shock and there is a 0.5 percent rise in consumption. The consumption effect is smaller than in the first scenario because a subset of people refinanced as interest rates declined and engaged in cash-out refinancing. Those people are generally not liquidity constrained in period seven.

These results show that, in our model, the current impact of monetary policy through the refinancing channel depends on the past actions of the Fed. The fundamental reason is that those actions affect the distribution of potential savings from refinancing.

8.2.2 A downside of long periods of low interest rates

Here we use our model to quantify an important cost of keeping interest rates low for a long period of time: it makes monetary policy less powerful for an extended period thereafter.

We begin by addressing the question: after rates have been normalized, when does monetary policy regain its initial potency? To address this question we consider the paths displayed in panel A of Figure 8. In all of these cases, the economy starts from steady state and the interest rate falls from 3.5 percent to 1 percent for four periods. The interest rate then normalizes back to 3.5 percent. The difference between the cases is that t periods after the normalization, $t \in \{1, 2, 3\}$, the interest rate falls by 50 basis points.

Results are reported in Table 10. From this table we see that aggregate consumption rises by 0.9, 0.9 and 1.3 percent for $t = 1, 2$, and 3, respectively. So the sooner the interest rate cut after normalization occurs, the smaller is its impact. For reference, recall that aggregate consumption rises by 1.3 percent if the interest rate falls by 50 basis points in the benchmark scenario where the economy is in steady state. So the potency of an interest rate cut is substantially reduced for the first two years after the interest rate is normalized, with the most dramatic effect in the first year.

The key factor driving this result is that fewer people face a positive interest-rate gap when the interest rate is cut relative to the benchmark scenario. Many people face a negative-rate gap because they entered mortgages at rates that were lower than the steady-state mortgage rate. So fewer people have an incentive to refinance their mortgages in period seven than in the benchmark scenario.

Over time, people enter new loans in response to life-cycle-related income changes and idiosyncratic-income shocks. So the share of people with a mortgage rate equal to the steady-state rate increases over time. That increase in turn implies that a larger fraction of people have a positive-rate gap after a 50 basis points rate cut. The potency of an interest rate cut rises over time. According to Table 10, it takes roughly three years for monetary policy to have the same effect on consumption as in the benchmark case.

Consistent with the post-normalization results, our model also implies that monetary policy is less potent when interest rates are low. To illustrate this point, suppose

that starting from steady state, the interest rate falls from 3.5 percent to 1 percent for four periods.[19] Then, in period six, the interest rate falls by an additional 50 basis points. According to our model, only 7 percent of people refinance in the impact period of the shock and there is only a 0.4 percent rise in consumption. These modest effects contrast sharply with the effect of an interest rate fall in the benchmark scenario where 26 percent of people refinance in the impact period of the shock and there is a 1.3 percent rise in consumption.

What can policy makers do to deal with the potency problem? One possibility is to take advantage of the nonlinear response of consumption to a fall in the interest rate. Recall that a 50 basis point interest rate cut in the first period after interest rates normalize leads to a 0.9 percent rise in consumption. Suppose instead that the interest rate fell by 100 basis points. Then consumption would rise by 2.4 percent. This increase is roughly the same if, starting from steady state, the interest rate falls by 100 basis.

These results suggest that policy makers can deal with the potency problem in one of two ways. If they cut interest rates by relatively small amounts, e.g. 50 basis points, then they wait until policy regains the same impact as in the steady state. However, if they are prepared to cut interest rates by large amounts, e.g. 100 basis points, the potency problem is not an issue.

9 Conclusion

This paper provides evidence that the efficacy of monetary policy is state dependent, varying in a systematic way with the pool of savings from refinancing. We construct a quantitative life-cycle model of refinancing decisions that is consistent with the facts that we document.

Our model points to an important cost of fighting recessions with a prolonged period

[19] As above, we model changes in interest rates via sequences of interest rate shocks. In all cases agents form expectations about aggregate states according to the Markov-chain approximation to the demeaned level representation of the aggregate states associated with equation (14).

of low interest rates. Such a policy reduces the potency of monetary policy in the period after interest rates are normalized. So, if the economy is affected by a negative shock during that period, policy makers will have less ammunition at their disposal to counteract the effects of that shock. This observation raises the conundrum: should monetary policy makers use their ammunition to fight an ongoing recession or the next one?

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Tables and Figures

Table 1: State dependency of monetary policy and refinancing

Refinancing over the year	**OLS** **(I)**	**IV** **(II)**
ΔR(t)	0.041***	0.040***
	(0.005)	(0.023)
ΔR(t) x Average rate gap	0.096**	0.266***
	(0.023)	(0.076)
County Fixed Effects	Yes	Yes
SPF Controls	Yes	Yes
Additional county controls	Yes	Yes

Notes: The table reports the response to a decline in interest rates. It therefore reports the estimates from regression equation (2), multiplied by -1. The IV is based on futures. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 2: First-stage estimates

First stage y-variable:	**ΔR(t)**	**ΔR(t) x A(t-1)**
	(I)	**(II)**
Panel A:		
Ɛ(t)	2.130***	0.491***
	(0.175)	(0.042)
Ɛ(t) x Average rate gap	1.093***	0.825***
	(0.231)	(0.156)

Notes: Regression equation (2), first-stage estimates based on futures shock. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 3: State dependency of monetary policy and cash-out refinancing

	OLS (I)	IV (II)
Panel A: Fraction cash-out refi		
ΔR(t)	0.070***	0.074***
	(0.003)	(0.007)
ΔR(t) x Average rate gap	0.073***	0.176***
	(0.005)	(0.027)
Panel B: Change in balance, given cash-out refi		
ΔR(t)	0.137***	0.237***
	(0.012)	(0.026)
ΔR(t) x Average rate gap	0.045*	0.215*
	(0.025)	(0.132)
County Fixed Effects	Yes	Yes
SPF Controls	Yes	Yes
Additional county controls	Yes	Yes

Notes: The table reports the response to a decline in interest rates. It therefore reports the estimates from regression equation (2), multiplied by -1. IV is based on futures. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 4: State dependency of monetary policy, unemployment and housing permits

	Change in unemployment rate over the year (I)	**Housing permit growth over the year (II)**
ΔR(t)	-0.034*	0.248***
	(0.014)	(0.043)
ΔR(t) x Average rate gap	-0.065***	0.234***
	(0.014)	(0.087)
County Fixed Effects	Yes	Yes
SPF Controls	Yes	Yes
Additional county controls	Yes	Yes

Notes: The table reports the response to a decline in interest rates. It therefore reports the estimates from regression equations (4) and (5), multiplied by -1. IV is based on futures. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 5: Model parameter values

Parameters		Value
σ	Intertemporal elasticity of substitution	2
δ	Housing depreciation rate	3%
ϕ	Collateral constraint	0.2
ρ_η	Persistency of idiosyncratic income process	0.91
σ_η	Variance of idiosyncratic income shock	0.21
α	Utility parameter	0.88
β	Discount rate	0.962
B	Bequest parameter	2

Notes: Table depicts parameter values. See text for more detail.

Table 6: Estimated Aggregate Process for Mortgage and Rental Rates

	Regression with dependent variable	
Variables	30-year rate$_t$	log rental rate$_t$
log y_t	-3.475***	0.843***
	(0.168)	(0.119)
log r_t	0.334***	-0.002***
	(0.058)	(0.001)
log p_t		-0.022
		(0.014)
constant	-0.030	3.187***
	(15.82)	(0.488)

Notes: Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels. See text for more detail.

Table 7: Estimated Aggregate Process

	Regression with dependent variable			
Variables	log y_t	log r_t	log p_t	log savings$_t$
log y_{t-1}	-0.272**	0.401***	-0.006	-2.715
	(0.108)	(2.845)	(0.047)	(0.147)
log r_{t-1}	0.071	0.900***	0.295***	12.130
	(0.108)	(0.051)	(0.002)	(0.147)
log p_{t-1}	0.119*	0.055	0.788***	1.177
	(0.075)	(2.114)	(0.070)	(1.710)
log savings$_{t-1}$	0.001	-0.002	0.011***	0.457*
	(0.006)	(0.142)	(0.008)	(0.296)
log savings$_{t-1}$ x log r_{t-1}	-0.073	-0.187***	-0.269***	-8.880**
	(0.002)	(0.035)	(0.002)	(0.086)

Notes: Regression equation (15). Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels. See text for more detail.

Table 8: State dependency of monetary policy and refinancing: Model vs Data

	Data	Model
Panel A: Fraction of loans that refinanced		
ΔR(t)	0.040***	0.038
	(0.023)	
ΔR(t) x Average rate gap	0.266***	0.299
	(0.076)	
Panel B: Fraction of loans that are cash-out refi		
ΔR(t)	0.074***	0.030
	(0.007)	
ΔR(t) x Average rate gap	0.176***	0.217
	(0.027)	
Panel C: Fraction of loans for home purchases		
ΔR(t)	0.162***	0.085
	(0.014)	
ΔR(t) x Average rate gap	0.147***	0.202
	(0.019)	

Notes: The table reports the response to a decline in interest rates. It therefore reports the estimates from regression equation (2), multiplied by -1. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 9: Alternative paths of monetary policy

Rate path prior to a 50bp cut	Average rate gap before cut	Fraction with positive rate gap, after rate cut	Effect on refinancing	Change in consumption	Fraction ST constrained
Panel A: Effects of Flat vs Rising History					
(i) Flat at about 3.5%	0.00%	100%	26%	1.3%	0.48
(ii) Rising from 3.5% to 6.5% over 4 pds	-0.81%	16%	5%	0.1%	0.64
Difference (i)-(ii)	0.81%	84%	21%	1.2%	-0.16
Panel B: Effects of Flat vs Falling History					
(i) Flat at about 3.5%	0.00%	100%	26%	1.3%	0.48
(ii) Falling from 3.5% to 1% over 4 pds	0.46%	100%	23%	0.5%	0.33
Difference (i)-(ii)	-0.46%	0%	3%	0.9%	0.15

Notes: Alternative paths of monetary policy. See text for more detail.

Table 10: Alternative paths of monetary policy

Rate path prior to a rate cut	Average rate gap before cut	Fraction with positive rate gap, after rate cut	Effect on refinancing	Change in consumption	Fraction ST constrained
Reloading Effect with 50bp cut					
(a) Benchmark case: continuously flat at 3.5% prior to a 50bp rate cut	0.00%	100%	26%	1.3%	48%
(b) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **1 pd**	-0.28%	66%	22%	0.9%	57%
(c) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **2 pds**	-0.27%	68%	26%	0.9%	58%
(d) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **3 pds**	-0.25%	70%	26%	1.3%	58%
Reloading Effect with 100bp cut					
(e) Benchmark case: continuously flat at 3.5% prior to a 100bp rate cut	0.00%	100%	27%	2.5%	47%
(f) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **1 pd**	-0.28%	67%	22%	2.4%	57%

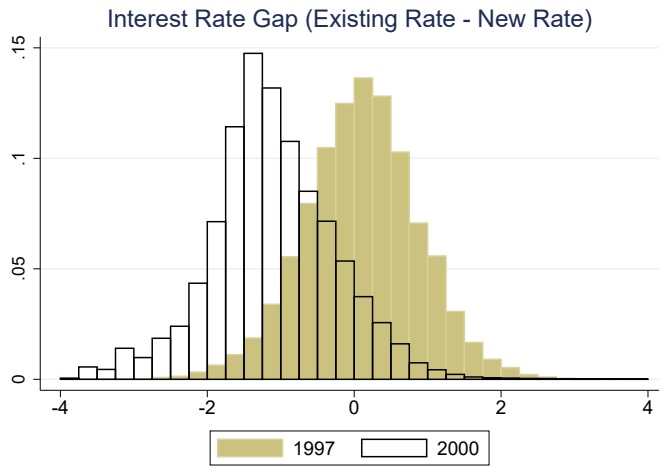
Notes: Alternative paths of monetary policy. See text for more detail.

Table 11: State dependency of monetary policy

Effect on refinancing:	
Overall effect of a 50 bp expansionary shock	5.53%
$\beta_1 \Delta R_t$	1.90%
$\beta_2 \Delta R_t$ times mean(φ_t)	3.63%
Effect on consumption:	
Overall effect of a 50 bp expansionary shock	2.05%
$\beta_1 \Delta R_t$	1.21%
$\beta_2 \Delta R_t$ times mean(φ_t)	0.85%

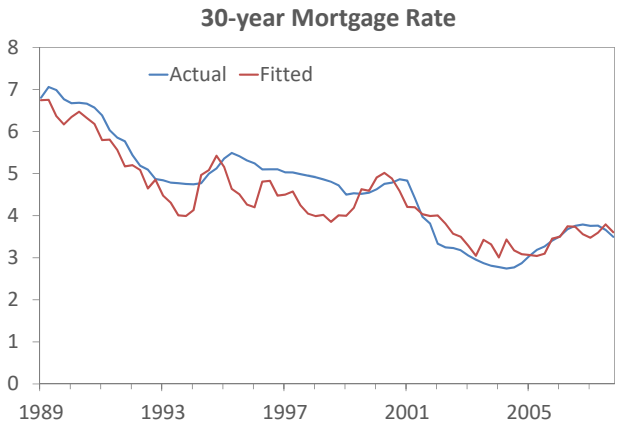
Notes: The table reports the response to a decline in interest rates. It therefore reports the estimates from regression equation (2), multiplied by -1. See text for more detail.

Figure 1: Distribution of interest rate gaps in 1997q4 and 2000q4



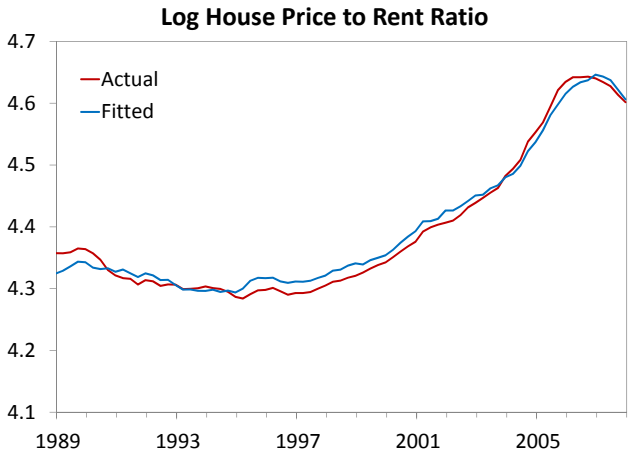
Notes: The figure depicts the distribution of interest-rate gaps across borrowers. The interest-rate gap is defined as the difference between the existing mortgage rate and the current market rate. See text for more details.

Figure 2: Time series of fitted and actual mortgage rates



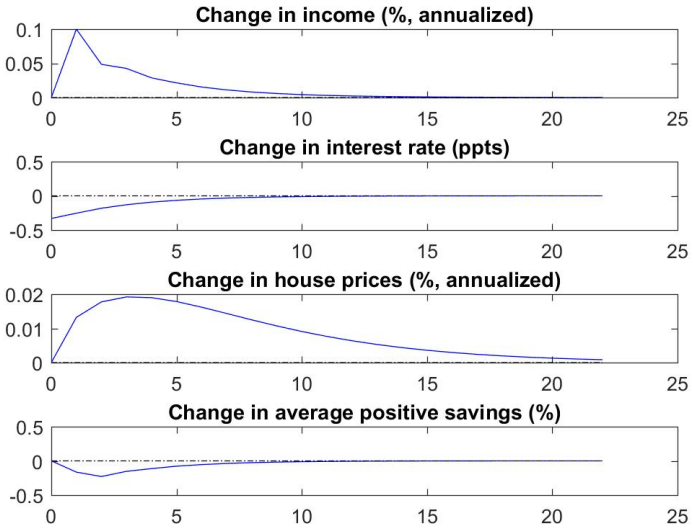
Notes: The figure depicts the fitted and actual mortgage rate data. See text for more details.

Figure 3: Time series of fitted and actual house price to rent ratios



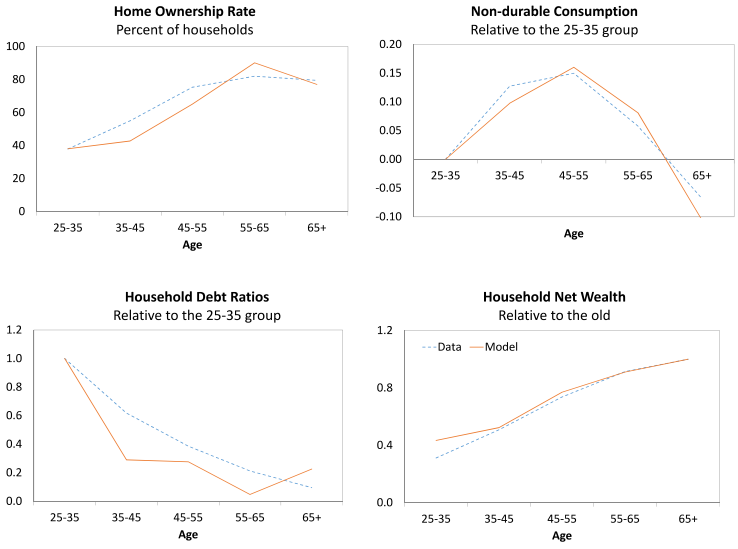
Notes: The figure depicts the fitted and actual house price to rental ratios. See text for more details.

Figure 4: Impulse response function of aggregate variables



Notes: The figure depicts the impulse response function to a 1 sd interest rate shock. See text for details.

Figure 5: Life-cycle moments

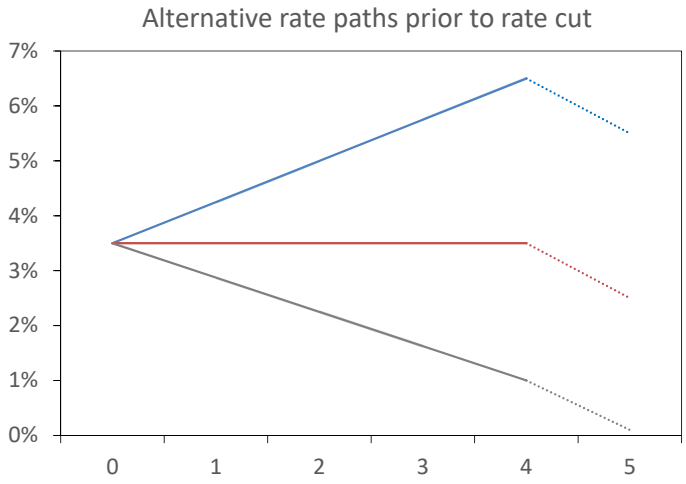


Notes: The figure depicts the fitted and actual life-cycle moments. See text for more details.

Figure 6: Refinancing, given the interest-rate gap

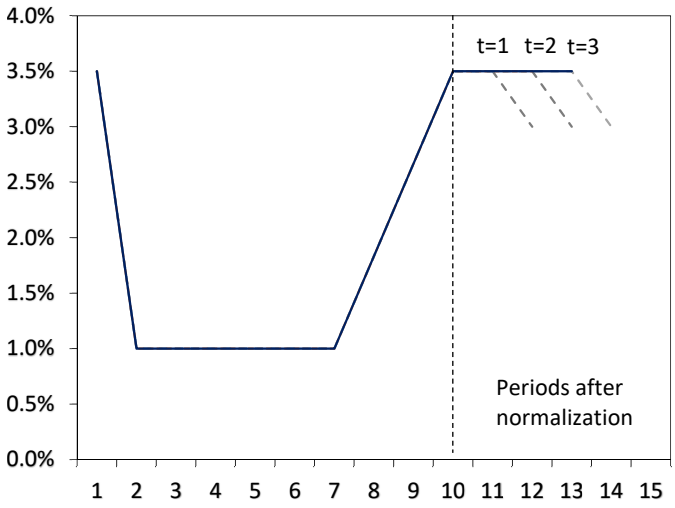
Notes: The figure depicts propensity to refinance for each given interest-rate gap in the data and the model. See text for more details.

Figure 7: Alternative interest rate paths



Notes: The figure depicts three alternative interest rate paths, starting at steady state. See text for more details.

Figure 8: Alternative interest rate paths



Notes: The figure depicts three alternative interest rate paths, starting at steady state. See text for more details.

Appendix

A County Data Description

In this section, we describe our data sources and the construction of the county-level demographic variables used in our analysis.

For each county, we obtain the median age and the share of the population with a college degree from the Census, the unemployment rate and share of employment in manufacturing from the Bureau of Labor Statistics, and per-capita income from the Bureau of Economic Analysis.

We measure lender competitiveness using the Hirschman-Herfindahl Index computed across mortgage lenders within the county.[20] This measure is also used in Scharfstein and Sunderam (2016). The index is constructed using data from HMDA (the Home Mortgage Disclosure Act).

We consider two measures of home values. Our first measure is the average home price accumulation over the life of the mortgage. We compute real house prices using the consumer price index. We then compute the log difference between the current home price and the value of the house at origination.

The median sale price of homes comes from two sources. We have monthly house-price data from the Global Financial Data Real Estate database from 1975 to present. The home prices are based on information from Freddie Mac and Fannie Mae. For house prices prior to 1975, we use regional data from the U.S. Bureau of the Census and U.S. Department of Housing and Urban Development. The two different data series have very similar trends in the overlapping post-1975 period.

We use individual data on home equity to compute the average level of home equity. For each loan, we compute home equity (price minus the balance). We then winsorize the top and bottom 1 percent of the home equity values to abstract from outliers.

[20] We thank David Berger for sharing these data with us.

Finally, we take an average across all loans within the county, weighted by loan balance.

B Robustness

B.1 Instrumenting with the 2-year Treasury Yield

This section provides additional estimates of the state dependent effects of monetary policy. In the main text, we instrumented for the response to a change in mortgage rate using high-frequency changes in the Federal Funds futures rate. Here, we show that the results are robust to instrumenting using the high-frequency changes in the 2-year Treasury yield within a 60-minute window around the Fed's announcement. Changes in the 2-year Treasury yield have been used as measures of monetary shocks by Gertler and Karadi (2013) and Gilchrist et al. (2015). Table 12 reports our estimates of regression specification (2), using the high-frequency changes in the 2-year Treasury yield as an instrument for changes in the mortgage rate. The estimated state dependent effects of monetary policy obtained using this alternative instrument are very similar to those reported in Tables 1 of the main text.

Table 12: State dependency of monetary policy and refinancing

	OLS (I)	IV (II)
ΔR(t)	0.041***	0.094***
	(0.005)	(0.011)
ΔR(t) x Average rate gap	0.096**	0.224
	(0.023)	(0.181)

Notes: Estimates from regression (2). IV based on changes in the 2-year Treasury yield. Standard errors are in parentheses. *, **, and *** give significance at 10, 5, and 1 percent levels.

B.2 Additional county-level controls

In this section, we show that our estimates of the state dependent nature of the effects of monetary policy are robust to the inclusion of interactions between county-level controls and the change in mortgage rates. These estimates, reported in Table 14 below, are similar to those in column 4 of Table 1, in the main text. The fact that including interaction terms does not change the estimate elasticities implies that the state dependency that we highlight is distinct from other potential mechanisms explored in the literature. These mechanisms include, for instance, differential responses in refinancing to a decline in mortgage rates due to differences in competitiveness of the local lending market. It is also distinct from state dependency related to variation in the value of home equity across counties.

Table 13: State dependency of monetary policy and refinancing

	(I)		(II)	
	coefficient	std error	coefficient	std error
ΔR(t) x Average rate gap(t-1)	0.266***	(0.076)	0.562***	(0.181)
ΔR(t) x Average savings(t-1)				
ΔR(t) x Home equity(t-1)			0.605	(0.584)
ΔR(t) x House price change(t-1)			-0.229	(0.171)
ΔR(t) x Unemployment rate(t-1)			-0.030	(0.016)
ΔR(t) x Median age(t-1)			-0.001	(0.003)
ΔR(t) x Manufacturing share(t-1)			0.008*	(0.003)
ΔR(t) x Share college(t-1)			0.155	(0.154)
ΔR(t) x ARM share(t-1)			-0.004	(0.176)
ΔR(t) x Herfindahl index(t-1)			0.023	(0.026)
County Fixed Effects	Yes		Yes	
County interaction controls	No		Yes	

Notes: Estimates from regression (3). For comparison, we report the coefficients from Table 1 (column 2) in the main text in this table's columns I and II. Column III is the estimated effects when we include the county demographics interacted with the change in mortgage rates. Standard errors are in parentheses. *, **, and *** give significance at 10, 5, and 1 percent levels.

B.3 Alternative moments

This section reports estimates of the state dependent effects of monetary policy using three alternative moments of the distribution of potential savings: the present value of potential savings, the fraction of loans with positive savings, and the spread of the existing mortgage rate relative to the threshold interest rate proposed by Agarwal, Laibson and Driscoll (2013). We find that the effects of a change in mortgage rates is state dependent, varying with the values of these alternative moments of the distribution.

First, we consider an alternative measure of the potential savings from refinancing

based on the present value of savings from pursuing the following simple refinancing strategy: the existing loan is refinanced with a FICO-specific 30-year fixed-rate mortgage and the new loan is repaid over the remaining life of the mortgage being refinanced. To simplify the notation, we suppress the dependence of the interest rate on FICO score and region.

Consider a 30-year mortgage with a fixed interest rate r^{old} that was originated at $T-30$ and matures at time T. The loan is repaid with fixed payments which we denote by Payment^{old}. These payments are given by:

$$\text{Balance}_{T-30} = \sum_{k=1}^{30} \frac{\text{Payment}^{old}}{(1+r^{old})^k}.$$

If the person refinances at the beginning of time t, before the mortgage payment is due, the balance owned on the old loan is given by the present value of the remaining payments:

$$\text{Balance}_t = \sum_{k=t}^{T} \frac{\text{Payment}^{old}}{(1+r^{old})^{(k-t)}}.$$

The balance of the new mortgage is the same as that of the old mortgage. The new mortgage payment is computed assuming that the mortgage is paid off over a 30-year period:

$$\text{Balance}_t = \sum_{k=1}^{30} \frac{\text{Payment}^{new}}{(1+r^{new})^k}.$$

The present value of savings associated with this refinancing strategy is:

$$\text{Savings}_t = \left[\sum_{k=t}^{T} \frac{\text{Payment}^{old} - \text{Payment}^{new}}{(1+r^{new})^{(k-t)}}\right] - \frac{\text{Balance}_T}{(1+r^{new})^{T-t}}, \tag{19}$$

where Balance_T is the balance of the refinanced mortgage at time T. We can rewrite equation (19) as:

$$\text{Balance}_t + \text{Savings}_t = \left[\sum_{k=t}^{T} \frac{\text{Payment}^{old}}{(1+r^{new})^{(k-t)}}\right].$$

This equation shows that if the household chooses its new mortgage so that the new mortgage payment is equal to the old mortgage payment, it can cash out Savings_t. They do so by borrowing Balance_t+Savings_t, and using Balance_t to pay the old mortgage. With this strategy, the household takes out a mortgage loan that is larger than the existing mortgage loan and receives the difference between the two loans in cash.

We convert our nominal measures of potential savings into real terms using the Consumer Price Index (base year 1999). We construct this measure of savings for every mortgage at time t. We then compute the average level of savings at time t. We denote the average level of savings across mortgages by A_{2t}:

$$A_{2t} = \frac{1}{n_t} \sum_{i=1}^{n_t} \text{Savings}_{it}. \tag{20}$$

The unconditional quarterly mean and standard deviation of the average savings from refinancing are -294 and $2,424$ dollars, respectively.

We now discuss the estimates of regression (2) obtained for the case where A^c_{t-1} is the average of savings from refinancing. Here, both β_1 and β_2 are significant at the one percent level. To interpret these coefficients, suppose that all the independent variables in regression (2) are initially equal to their time-series averages and that average of savings are initially equal to its mean value of $-\$294$. Our estimates in column 2 of Panel A of Table 14 imply that a 25 basis points drop in mortgage rates raises the share of loans refinanced by about 7.2 percent. Now suppose that the drop in mortgage rates happens when the average savings from refinancing is equal to $\$2,130$, which is the mean value of $(-\$294)$ plus one standard deviation $(\$2,424)$. Then, the refinancing rate rises to 10.4 percent. So, the marginal impact of a one standard-deviation increase in the average savings from refinancing is 2.5 percentage points.

Panels B and C of Table 14 consider two additional alternative moments of refinancing savings: the fraction of loans with positive savings, and the spread of the existing mortgage rate relative to the threshold interest rate proposed by Agarwal, Laibson and Driscoll (2013). We again find that the effects of a change in mortgage rates is state

dependent, varying with the values of these alternative moments of the distribution.

C Model aggregate process

In our model, we assume that the aggregate state variables (log of aggregate income, log of house prices, and log of the real interest rate) evolve according to the vector autoregression process described in Equation (16), Section 6.2:

$$\triangle S_t = B_1 \triangle S_{t-1} + B_2 \triangle \log\left(r_{t-1}\right) a_{t-1} + u_t$$

where B_1 is a 4×4 matrix, B_2 is a 4×1 vector, and u_t is a Gaussian disturbance.

We now provide evidence that the process does well relative to other specifications, in terms of the root-mean-squared error (RMSE). Table 15 below shows that none of the RMSE associated with the alternative specifications is smaller, taking sampling uncertainty into account, than the RMSE associated with specification (16). At the same time, specification (16) does have a statistically significant smaller RMSE than many alternative specifications.

The standard errors are computed as follows. We draw a set of coefficients from the joint distribution of estimated coefficients. We use the set of coefficients to construct one-step-ahead forecasts and compute the RMSE. We repeat these two steps for 100,000 draws of coefficients, and then compute the standard error of the RMSE.

D Model computation

To solve the model numerically, we implement the following procedure. First, we reformulate the choice variables to rectangularize the problem and simplify computational issues that arise from the endogenous mortgage constraint. The problem is reformulated in terms of the leverage ratio, defined as

$$q_{jat} = b_{jat}/p_t h_{jat} \geq 0.$$

Table 14: State dependency of monetary policy and refinancing

Refinancing over the year	**OLS**	**IV**
	(I)	**(II)**
Panel A		
ΔR(t)	0.045***	0.081***
	(0.005)	(0.017)
ΔR(t) x Average savings	0.021**	0.028**
	(0.004)	(0.009)
Panel B		
ΔR(t)	-0.022	-0.004
	(0.033)	(0.063)
ΔR(t) x Fraction positive rate gap	0.140**	0.183*
	(0.058)	(0.111)
Panel C		
ΔR(t)	0.118***	0.253***
	(0.030)	(0.088)
ΔR(t) x Spread of old rate to ADL threshold	0.069**	0.163*
	(0.028)	(0.089)
County Fixed Effects	Yes	Yes
SPF Controls	Yes	Yes
Additional county controls	Yes	Yes

Notes: Estimates from regression (3). IV is based on futures. Standard errors are in parentheses. 10, 5, and 1 percent significance levels are denoted by *, **, and ***, respectively.

Table 15: Root-mean-squared forecasting errors of regressions

Regression	**RMSE**	**SE**
$\triangle S_t = B_1 \triangle S_{t-1} + B_2 \triangle r_{t-1} a_{t-1} + u_t$	0.233	0.035
$\triangle S_t = B_1 \triangle S_{t-1} + u_t$	0.221	0.004
$\triangle S_t = B_1 \triangle S_{t-1} + B_2 \triangle S_{t-2} + u_t$	0.293	0.008
$\triangle S_t = B_1 \triangle S_{t-1} + B_2 \triangle S_{t-1} a_{t-1} + u_t$	0.309	0.099
$S_t = S_{t-1} + B_1 S_{t-1} A_{t-1} + u_t$	0.258	0.066

We solve the budget constraint for consumption and replace consumption in the utility function. The choices variables are therefore $s_{jat}, h_{jat}, 1(\text{rent})_{jat}, 1(\text{adjust})_{jat}, q_{jat}$. We discretize the idiosyncratic income variable y_{jat}. We simulate the quarterly process for the aggregate state vector, S_t, to obtain the annual probability transition matrix for S_t. We discretize S_t using the Rouwenhorst method. There are 32 grid points for S_t and two grid points for y_{jat}. The value functions ($V^{\text{own \& noadjust}}(z_{jat})$, $V^{\text{own \& adjust}}(z_{jat})$ and $V^{\text{rent}}(z_{jat})$) are approximated as multilinear functions in the states, where $z_{jat} = [S_t, y_{jat}, \text{assets}_{jat}]$. There are four endogenous states $\text{assets}_{jat} = \left[s_{jat}, h^o_{jat}, b_{jat}, r_{jat}\right]$. We use 10 knots for b_{jat}, s_{jat}, and h^o_{jat}, and 5 knots for r_{jat}. The knots are spaced more closely together near the constraints for b_{jat} and s_{jat}. The value functions are interpolated between knots.

The model is solved via backward induction from the final period of life. At each age and each case, the optimal policies are computed using a Nelder-Meade algorithm, comparing the value functions for each of the three cases (to rent, to own a home and adjust the mortgage, to own a home and not adjust the mortgage) to generate the

overall policy function.

To estimate the regression used in our empirical section with data simulated from the model, we proceed as follows. The model is initialized with the same distribution of wealth and mortgage rates for 1994, obtained from the Survey of Consumer Finances and the Core Logic database. We then feed the actual path for house prices, aggregate income, and interest rates for the period 1994-2007. Each cohort faces the historical path for the state variables, as well as the realized aggregate state variables. Given their individual and aggregate states, they make their consumption, mortgage, housing, and savings decisions. Given the observed decisions and states, we estimate the regression used in our empirical work and compare our model-based estimates with the empirical estimates.