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 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 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 1 percent rise in consumption. In contrast, when this gap is one standard deviation above the mean, then consumption rises by 1.4 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 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.

We build on Wong (2020) who studies how the impact of monetary policy shocks on consumption varies by age and mortgage decisions. She finds that mortgage decisions, including refinancing, are a key determinant of why consumption responses to monetary policy shocks vary by age. Our contributions relative to Wong (2020) are two-fold. First, we document and model the state-contingent nature of refinancing decisions and its implications for the efficacy of monetary policy. Second, we focus on how the history of interest rates affects the potency of monetary policy. In pursuing these objectives, we must overcome the challenge of allowing for state-dependent effects of monetary policy in a structural model. The basic issue is that to make their decisions people must form expectations about future income, mortgage rates, house prices, and rental rates. The stochastic processes for these variables are state dependent, so our model solution technique must accommodate this dependency.

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 in 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 by an extended period of low interest rates. Section 9 provides some conclusions.

2 Related literature

Our paper relates to five strands of literature. The first strand is a classic literature on the effect of changes in interest rates on mortgage refinancing. Dunn and McConnell (1981) develop a theoretical model for pricing mortgage-backed securities that takes into account the effect of refinancing on the prices, risks and expected returns of such securities. In an early empirical contribution, Green and Shoven (1986) use a proportional hazard model to estimate the reduction in the probability of prepayment of fixed-rate mortgages associated with interest rate changes. Schwartz and Torous (1989) extend the Green and Shoven (1986) analysis to include the effects of seasoning, lagged refinancing rates, heterogeneity in borrowers, and seasonal effects. They use the resulting model to study the effect of prepayment on the valuation of mortgage-backed securities. Recent contributions to this literature study the distribution of mortgage rates across borrowers and emphasize the role of transaction costs and inattention in explaining refinancing decisions. Examples include Andersen et al. (2015) and Bhutta and Keys (2016). In this paper, we extend the existing literature by studying how the distribution of mortgage rates generates state dependency in the effects of monetary policy.

The second strand of the literature 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).

Because young households tend to be borrowers, while old households tend to invest in long-term bonds, monetary policy has potentially important distributional effects. Our paper is related to a third strand of the literature on the distributional effects of inflation (see Doepke and Schneider (2006) and Doepke, Schneider and Selezneva (2018) and the references therein). 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 fourth strand of literature focuses on the role of the mortgage market in the transmission of monetary policy. Iacovelo (2005), Garriga, Kydland and Sustek (2017) and Greenwald (2018) model the transmission mechanism using a representative borrower and saver model. In contrast, we use a 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), Iacovello and Pavan (2013), Auclert (2017), Berger, Guerrieri, Lorenzoni, and Vavra (2017), Garriga and Hedlund (2017), Guren, Krishnamurthy, and McQuade (2017), Guren, McKay, Nakamura, and Steinsson (2018), Kaplan, Mitman, and Violante (2017), Kaplan, Moll, and Violante (2018), and Wong (2020)).

Finally, 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 the previous literatures, 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 important in the aftermath of the financial crisis. But we also think that demand-side considerations were important prior to the crisis and will become increasingly important as credit markets return to normal.

3 Data

Our empirical work is primarily based on CoreLogic Loan-Level Market Analytics, a loan-level panel data set with observations beginning in 1995 which includes loan-level analytics mortgage and origination data. 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)).

The CoreLogic data includes 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). There is no information on the purpose of a small fraction of the loans (5 percent). We compute the fraction of mortgages refinanced as the ratio of mortgages that are refinanced to the total number of mortgages outstanding. This measure is conservative in the sense that some of the loans whose purpose is unknown to us could have been used to refinance existing mortgages.

For each borrower, we obtain county-level demographic information, including age

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

structure, share of employment in manufacturing, lender competitiveness, measures of home-equity accumulation, educational attainment, unemployment, and per capita income. Appendix A contains a description of these variables. We also obtain county-level housing permits from the Census Building Permits Survey and county-level unemployment rates from the Current Population Survey.

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. Cash-out refinances are identified by the Freddie Mac loan-purpose flag. These data are available since 1999.

Throughout, we confine our analysis to fixed-rate 30-year mortgages. Our results are robust to considering mortgages of different maturities. Figure 1 displays the level and first differences of the fraction of mortgages that are refinanced and the fraction of refinanced mortgages that are cash-out.

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, and income per capita from the Federal Reserve Bank of St. Louis. National house prices are obtained from Mack and Martínez-García (2011). Rental rates are obtained from the Organization for Economic Cooperation and Development.

Finally, we obtain measures of expected inflation from the Federal Reserve Bank of Cleveland. Nominal variables are converted to real variables using the consumer price index. We obtain county-level house price data from two sources. House price data is obtained from Hurst et al (2019). These authors obtain the data from the Federal Housing Finance Authority (FHFA). Our second source of house price data, which is used to construct home equity, is obtained from the Global Financial Data Real Estate database. The database contains house price data on monthly loans purchased by Freddie Mac or Fannie Mae within each region.

Lender competitiveness data was constructed by Scharfstein and Sunderam (2016), using Home Mortgage Disclosure Act (HMDA) data.

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 old and new mortgage interest rates, outstanding mortgage 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 alternative mortgage rate that household i could refinance at.

We compute the average, across households, 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 variable n_t denotes the number of mortgages outstanding at time t. A_t is a real variable, since it is based on the difference between two nominal interest rates. A virtue of 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 characteristics of the new mortgage (e.g. duration and fixed versus variable interest rates).

The new mortgage rate depends on borrower characteristics, including FICO and region. We group FICO scores into the following bins: below 600, $600-620$, $620-640$,... ,...,$760-780$, and greater than 780. 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] We also considered versions of r_{it}^{new} that condition in

[2]As a practical matter, we find that our results are robust to not conditioning on the household's

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}^{new} to fit the distribution of interest rates across new borrowers.

The annualized unconditional quarterly mean and standard deviation of A_t is -14 basis points and 70 basis points, respectively. The distribution of the interest rate gap varies considerably over time. To make this point concrete, Figure 2 displays the distribution of interest-rate gaps in 1997.Q4 and 2000.Q4. These dates correspond to local turning points in the average real mortgage rate. The fraction of households with positive savings and the average savings is much higher in 1997.Q4 than in 2000.Q4.

In Appendix C3, 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 to using these alternative measures.

The average cross-sectional dispersion in the average rate gap is 1 percent. In Appendix B, we report the correlation between the average rate gap and observable characteristics (unemployment rate, per capita income, share of college educated, home equity accumulation, median age, manufacturing share, and share of males in the population). Other things equal, the average rate gap is higher in areas with a higher unemployment rate and it is a decreasing function of per capita income, the share of the population that is college educated, and the amount of home equity accumulation.

5 Empirical results

In this section, we study how the impact on refinancing activity of a change in the mortgage rate depends on the average savings from refinancing. We report basic cor-

region. This finding is consistent with Hurst, Keys, Seru and Vavra (2016) who find little evidence of spatial variation in mortgage rates.

relations based on ordinary least squares (OLS) in Appendix D. Here, 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. Our main results are that this marginal effect is state dependent as is the impact of a fall in interest rates on economic activity.

5.1 State dependency and refinancing activity

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 Z^c_{t-1} includes the following county-level controls: the unemployment rate, average log-change in real home equity, one-year lag of the refinancing rate, and a Herfindahl index of the mortgage sector. 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 on refinancing 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

[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.

cross-sectional and time-series variation in the response of refinancing to interest rate changes.[4]

We estimate regression (2) using two instruments for ΔR_t^M that exploit exogenous changes in monetary policy.[5] 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 Federal Open Market Committee (FOMC) announcements.[6]

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

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

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 term $D/(D-t)$ 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.

[4] 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.

[5] It is difficult to give a causal interpretation to the OLS-based estimates of β_1 and β_2 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_t^M and $\Delta R_t^M \times A_{t-1}^c$ would be positively correlated with η_t^c creating a downward bias in β_1 and β_2.

[6] This approach has been used by Kuttner (2001), Gürkaynak, Sack and Swanson (2005), Cochrane and Piazessi (2002), Nakamura and Steinsson (2018), Gorodnichenko and Weber (2015), and Wong (2020), among others.

The standard deviation of the implied monetary policy shock is 12 basis points.

In Appendix C2, we report our empirical analysis when we measure a monetary policy shock using the 2-year Treasury yield:

$$\varepsilon_t = y_{t+\triangle^+} - y_{t-\triangle^-}.$$

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 28 basis points. Taking sampling uncertainty into account, this estimate is consistent with those of Gertler and Karadi (2015, Table 1), which range from 17 to 48 basis points, depending on the set of instruments used to identify the monetary shock.

Second, we estimate the following first-stage regressions:

$$\begin{aligned} \Delta R_t^M &= \alpha_0 X^c + \alpha_1 \varepsilon_t + \alpha_2 \varepsilon_t \times A_{t-1}^c + \alpha_3 Z_{t-1} + \alpha_4 Z_{t-1}^c + \eta_{1t}, \\ \Delta R_t^M A_{t-1}^c &= \gamma_0 X^c + \gamma_1 \varepsilon_t + \gamma_2 \varepsilon_t \times A_{t-1}^c + \gamma_3 Z_{t-1} + \gamma_4 Z_{t-1}^c + \eta_{2t}. \end{aligned}$$

Table 1 reports our first-stage regression estimates. The F test for the joint significance of the regression coefficients is greater than ten. This result is consistent with the view that monetary policy shocks are strong instruments. We also perform the Stock-Yogo (2005) test for the null hypothesis of weak instruments. The test statistic is 79.5, which firmly rejects the null of weak instruments.

Panel A of Table 2 reports results based on estimating regression (2) using instrumental variables. 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. Estimated parameters on controls are reported in Appendix C3. That appendix also documents the robustness of the estimated value of β_1 to including various lagged values of the refinancing rate in our empirical specification. Appendix D contains the analogue of Panel A of Table 2 generated using OLS.

To interpret the coefficients in Panel A of Table 2, 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 unconditional average share of loans that is refinanced is 7.9 percent. The estimates in Panel A of Table 2 imply that a 25 basis point drop in mortgage rates raises the share of loans that is refinanced to 8.0 percent.[7] Now, suppose that the drop in mortgage rates occurs when the average interest-rate gap is equal to 56 basis points. The latter 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 is refinanced to 12.6 percent.[8] So, the marginal impact of a one standard-deviation increase in the average interest-rate gap is 4.6 percent. This effect is large relative to the average annual refinancing rate, 7.9 percent.

Figure 3 reports the impulse response function of the fraction of mortgages refinanced to a 50 basis point drop in the mortgage rate. We compute this function for two cases corresponding to whether the average interest-gap is initially equal to −14 basis points or to 56 basis points. Panel A shows that in the first case there is a weak response of refinancing to the interest rate cut. Panel B shows that in the second case there is a persistent rise in refinancing activity over a two-year period.

A natural question is whether there is substantial variation over time in the impact of mortgage rate reductions on refinancing rates. To answer this question, we use the estimated version of regression (2) to calculate the effect of a 50 basis points reduction in the mortgage rate on the refinancing rate at each point in time in our sample. The solid line in Figure 4 plots this effect and the dashed lines correspond to the 95 percent confidence interval (computed using the delta method). There is substantial variation

[7]This value is given by $7.9\% + 0.25 \times (\beta_1 + \beta_2 \times -0.14) = 8.0\%$.

[8]This value is given by $7.9\% + 0.25 \times (\beta_1 + \beta_2 \times 0.56) = 12.6\%$.

in the potency of monetary policy through the refinancing channel. This effect was most potent in 1998 and 2003 and least potent in 1995 and 1999. These dates correspond to periods in which the average rate gap is high and low, respectively. We discuss our model's implication for these effects in Section 5.

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 Appendix C3. The implied estimates of β_2 are statistically indistinguishable from those reported in Panel A of Table 2. 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.

We find that our results are robust to including as additional controls the lag of the refinancing rate, the fraction of mortgages in county c that have adjustable mortgage rates, and the interaction of this variable with the monetary policy shock. Our results are also robust to including interactions between the monetary policy shock and slow-moving county characteristics such as the median age, share of employment in manufacturing, and share of college educated workers.

5.2 Cash-out refinancing

In this subsection, we use Freddie Mac 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. Mian and Sufi (2014) show that households predominantly use this type of refinancing to increase their consumption. So, cash-out refinancing plays an important role in 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 B of Table 2 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 Panel B of Table 2 imply that a 25 basis point 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 occurs when the average interest-rate gap is 56 basis points. Then, a 25 basis point 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 mortgages with cash-out refinancing. Panel C of Table 2 reports our results. 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-rate gap is initially equal to its mean value of -14 basis points. The estimates in panel C of Table 2 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 occurs when the average interest-rate gap is 56 basis points. Then, a 25 basis point 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 $\$123,000$. It follows that a 3.8 percent increase in mortgage balance 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. 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.

Our first measure of economic activity is the county-level unemployment rate. Our second measure is the number of county-level permits required for new, privately-owned residential buildings. This series, produced by the Census Building Permits Survey since 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. We aggregate these monthly data to a quarterly frequency.

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

$$\Delta \text{Unemployment}^c_{t,t+4} = \theta_0 X^c + \theta_1 \Delta R^M_t + \theta_2 \Delta R^M_t \times A^c_{t-1} + \theta_3 A^c_{t-1} + \theta_4 Z_{t-1} + \theta_5 Z^c_{t-1} + \eta^c_t,$$

where Z_t includes the same controls used in equation (2) except for the unemployment rate.

Table 3 reports our IV estimates obtained using the instruments discussed in Section 4.1. 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 (4) are initially equal to their time-series averages. Our estimates imply that a 25 basis point drop in mortgage rates lowers the unemployment rate by 0.6 percent. Suppose that the drop in mortgage rates occurs when the average interest-rate gap is equal to 56 basis points. Then a 25 basis point 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 percent.

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

$$\Delta \log \text{ Permits}^c_{t,t+4} = \theta_0 X^c + \theta_1 \Delta R^M_t + \theta_2 \Delta R^M_t \times A^c_{t-1} + \theta_3 A^c_{t-1} + \theta_4 Z_{t-1} + \theta_5 Z^c_{t-1} + \eta^c_t. \quad (4)$$

Table 3 reports our IV estimates. Both θ_1 and θ_2 are statistically significant at a 1 percent significance level. To interpret the point estimates suppose that all independent variables in regression (4) are initially equal to their time-series averages. The estimates in column 2 imply that a 25 basis point drop in mortgage rates raises the percentage change in new permits to 17.0. Now suppose that the drop in mortgage rates occurs when the average interest-rate gap is equal to 56 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 percent. This effect is large relative to a one standard deviation change in housing permits (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 the 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 generalizes the framework in Wong (2020) to allow for state dependency in the aggregate state process for the interest rate, income, house prices and rental rates. This generalization allows us to incorporate state-dependent feedback effects of monetary policy shocks on aggregate variables.

We use the model for three 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.

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 substantial heterogeneity in unobserved fixed costs of refinancing. An alternative is to model 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

[9]Recent work that emphasizes the correlation between household consumption and interest rate changes for understanding the behavior of aggregate consumption includes Auclert (2017), Kaplan, Violante and Moll (2018), and Wong (2020).

on surviving, people work for 40 years and retire for 20 years. The upper bound on a person's life is 85 years ($T = 85$).

The momentary utility of person j who is a periods old at 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 who is a periods old at time t. People derive housing services from either renting or owning a house. Renters can freely adjust the stock of rental housing in each period. To buy a home of size h, households pay a transaction cost $\Phi^{\text{new}}(h)$. To refinance an existing mortgage, homeowners pay a lump-sum transaction cost Φ^{refi}.[10] The stock of housing depreciates at rate δ. There are no transactions costs from changes in the housing stock associated with depreciation of an existing home. There are no adjustment costs associated with selling a house.

Upon death, the wealth of person j who is a periods old at time t, W_{jat}, is passed on as a bequest. If a person 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. Person j derives utility $B\left(W_{jat}^{1-\sigma} - 1\right)/(1-\sigma)$ from this bequest. Here B is a positive scalar. The presence of a bequest motive allows the model to be consistent with the fact that many people die with large amounts of assets (see e.g. Huggett (1996) and De Nardi and Yang (2014)). More importantly, this motive helps the model generate the fall in consumption and house downsizing that we observe in data for older consumers. The reason is that, as people get older, the bequests receive a higher weight in the utility function relative to consumption and housing.

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

$$\log(y_{jat}) = \chi_a + \eta_{jt} + \phi_a \log(y_t). \tag{5}$$

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

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 standard deviation, 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 $m(a)$.

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

$$M_{ja\tau} = \frac{b_{ja\tau}}{\sum_{k=1}^{m(a)} (1 + R_{ja\tau})^{-k}}. \tag{6}$$

If a person refinances or buys a new house at time t, the new mortgage rate is given by the current fixed mortgage rate:[11]

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

[11]In practice, U.S. mortgage rates can depend on the size of the loan. For example, jumbo mortgages (loans sizes that exceed the maximum guaranteed by Fannie Mae and Freddie Mac) have higher interest rates than non-jumbo mortgages. To simplify, we abstract from this feature in our analysis.

Bond holdings. A person can invest in a one-year bond that yields an interest rate r_t. The variable s_{jat} denotes the time-t bond holdings of person j who is a years old at time t. 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 in our model are $z = \{a, \eta, K, S\}$. 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, 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 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 mortgage interest rate, r_t^m, is given by

$$r_t^m = a_0^m + a_1^m \log(r_t) + a_2^m \log(y_t). \tag{7}$$

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 real rental rate is given by:

$$\log(p_t^r) = \ \alpha_0 + \alpha_1 \log(r_t) + \alpha_2 \log(y_t) + \alpha_3 \log(p_t). \tag{8}$$

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

$$V(z) = \max\left\{V(z)^{\text{rent}}, V(z)^{\text{purchase}}, V(z)^{\text{own \& refi}}, V(z)^{\text{own \& no refi}}\right\}. \tag{9}$$

A renter maximizes

$$V(z)^{\text{rent}} = \max_{c, h^{\text{rent}}, s'} u\left(c, h^{\text{rent}}\right) + \beta E\left[\pi_a V(z') + (1-\pi_a) B \frac{\left(W'\right)^{1-\sigma} - 1}{1-\sigma}\right], \tag{10}$$

subject to the budget constraint,

$$c + s' + p^r h^{\text{rent}} = y + (1-\delta) p h^{\text{own}} + (1+r)s - b(1+R), \tag{11}$$

and the borrowing constraint on short-term assets,

$$s' \geq 0.$$

The discount rate and the probability of survival are denoted by β and π_a, respectively. The term $B\left[\left(W'\right)^{1-\sigma} - 1\right] / (1-\sigma)$ represents the utility from bequests. The terms $(1-\delta)ph^{\text{own}}$ and $b(1+R)$ in equation (11) take into account the possibility that the renter was a home owner at time $t-1$. The renter's housing stock and mortgage debt are both zero:

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

A household who decides to purchase a new home maximizes:

$$V(z)^{\text{purchase}} = \max_{c,s',b'} u\left(c, h'^{\text{own}}\right) + \beta E\left[\pi_a V(z') + (1-\pi_a) B \frac{\left(W'\right)^{1-\sigma} - 1}{1-\sigma}\right],$$

subject to the budget constraint

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

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:

$$R' = r^m.$$

A homeowner who does not refinance his mortgage maximizes:

$$V(z)^{\text{own \& no refi}} = \max_{c,s'} u\left(c, h^{\text{own}}(1-\delta)\right) + \beta E\left[\pi_a V(z') + (1-\pi_a) B \frac{\left(W'\right)^{1-\sigma} - 1}{1-\sigma}\right], \tag{12}$$

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 (6). The law of motion for the housing stock is

$$h'^{\text{own}} = (1-\delta)h'.$$

A homeowner who refinances, maximizes:

$$V(z)^{\text{own \& refi}} = \max_{c,s',h'^{\text{own}},b'} u\left(c, h^{\text{own}}(1-\delta)\right) + \beta E\left[\pi_a V(z') + (1-\pi_a)B\frac{\left(W'\right)^{1-\sigma} - 1}{1-\sigma}\right],$$

subject to the budget constraint

$$c + s' - b' + \Phi^{\text{refi}} = y + (1+r)s - b(1+R),$$

the borrowing constraint on short-term assets,

$$s' \geq 0,$$

and the minimal down payment required on the mortgage,

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

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 4. We set $\sigma = 2$ 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+) according to 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. Residual earnings are the error term in a regression of the logarithm of individual income on age and aggregate income.

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 (7)) and and rental rates (α_0, α_1, α_2, and α_3 in equation (8)). We discuss the empirical fit of these processes in Section 6.2.

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 of a person's life are calibrated to match average assets and income for persons of ages 20 to 29 in the 2004 Survey of Consumer Finances. Mortgage rates are initialized according to the initial empirical distribution of mortgage rates.

We set the fixed cost of refinancing, Φ^{refi}, equal to $\$2,100$ (2 percent of median house price) to match the average quarterly fraction of new loans (4.5 percent). This value is consistent with the range of costs provided in the Federal Reserve's "Consumer Guide to Mortgage Refinancings" and with the evidence in LaCour-Little (2000).[12] The fixed costs of refinancing include the appraisal fee, the inspection fee, and the attorney review fee. The transaction cost function Φ^{new} for buying a new home has a fixed component,

[12]https://www.federalreserve.gov/pubs/refinancings

equal to \$1,100, and a variable component, equal to 4 percent of the house price. These value is consistent with empirical evidence as well as the values used in the literature.[13] Given this calibration, the model is consistent with the average rate of home ownership in the data.

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 base their expectations on a time-series model 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 (7)). We estimate this function using OLS. Table 5 reports our estimates. Figure 5 shows that the estimated version of equation (7) does a very good job at accounting for the time-series behavior of the 30-year mortgage rate over the period 1989-2008.

As discussed above, it is hard for traditional asset-pricing models to account for the empirical relation between rental rates and housing prices (see, e.g., Piazzesi and Schneider (2016)). So, we model the real rental rate as a linear function of r_t, y_t and p_t (see equation (8)). We estimate this function using the national house price and rent indices obtained from the Federal Reserve Bank Dallas. Figure 6 shows that the estimated version of equation (8) does a very good job at accounting for the time-series behavior of the logarithm of the house price-to-rent ratio over the period 1989-2008.

We estimate a suite of quarterly time-series models for the aggregate-state vector $S_t = \{\log(r_t), \log(y_t), \log(p_t), \log(A_t)\}$. We eliminate from consideration models with explosive dynamics and judged the remaining models balancing parsimony and the implied average (over time and across variables) root-mean-square-error (RMSE) of

[13] See Diaz and Luengo-Prado (2012) and Berger et al. (2015).

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:

$$\Delta S_t = B_0 + B_1 \Delta S_{t-1} + B_2 \Delta \log(r_{t-1}) a_{t-1} + u_t. \tag{13}$$

Here, B_1 is a 4×4 matrix, B_0 and B_2 are 4×1 vectors, and u_t is a 4×1 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 E 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 various measures of the gains from refinancing. For example, we replaced a_t with the average savings (in levels), the median savings, the average interest-rate gap, and the logarithm of average positive interest-rate gap, the median of the interest-rate gap, the fraction of mortgages with positive savings, and the standard deviation of savings. To conserve on space we do not report these results.

None of the RMSEs associated with the alternative specifications was smaller, taking sampling uncertainty into account, than the RMSE associated with specification (13). Specification (13) did have a statistically significant smaller RMSE than many of the alternatives.

Table 6 reports point estimates and standard errors for B_1 and B_2 associated with specification (13) estimated using quarterly data. The coefficients in B_2 are statistically significant at the one percent level for $\log(r_t)$ and $\log(p_t)$ and at the 5 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 (13) helps reduce the RMSE for the three aggregate variables, $\log(r_t)$, $\log(y_t)$, and $\log(p_t)$. Simply adding a_t to a linear VAR for $\log(r_t)$, $\log(y_t)$, and $\log(p_t)$, reduces the average

RMSE for $\log(r_t)$, $\log(y_t)$, and $\log(p_t)$ 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 $\log(r_t)$, $\log(y_t)$, and $\log(p_t)$.

We compute the impulse response of S_t to a monetary policy shock implied by (13) 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 7 displays the associated impulse response functions for a one-standard-deviation shock to monetary policy. We see that an expansionary monetary policy shock 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 (13) to zero and work with the implied VAR for the level of the variables. This procedure is equivalent to estimating the VAR using data that have been demeaned. We approximate this VAR with a Markov chain using the procedure described in Appendix F. We then convert the quarterly VAR into an annual VAR by raising the transmission function to the power four. 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 $\log(p_t)$ for the period 1995-2007. We simulate the idiosyncratic component of income, y_{jat}, for each household in our model.

Given the estimated VAR, the housing Sharpe ratio implied by the model is 2.46.[14] This value is similar to the Sharpe ratio of 2.53 implied by the NIPA Fixed Asset Tables 2.1, line 68 for the period 1994-2007.

One possible concern is that our model abstracts from the idiosyncratic shocks to home prices emphasized by Landvoigt, Piazzesi, and Schneider (2015). Incorporating idiosyncratic risk into the model would greatly increase the computational complexity of our analysis. To assess the robustness of our results to more volatile house prices, we increase the volatility of house-price shocks by 50 percent. Our main results regarding the state-dependent nature of monetary policy are robust to this perturbation. More volatile house prices make housing a riskier asset and deter home ownership. However, that volatility does not have a first-order effect on refinancing decision.

7.1 Life-cycle dynamics.

Consider the model's ability to account for how the behavior of U.S. households evolves with age. Figure 8 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 at accounting for the key features of these data. Notably home ownership rates rise with age and stabilize when people reach their 40s, both in the model and the data.

To understand the mechanisms that underlie the dynamics of home-ownership, it is useful to consider a simplified analysis of the cost of owning versus renting.[15] The net benefit of owning a home is given by:

$$\frac{p_t^r}{p_t} + E_t \frac{p_{t+1} - p_t}{p_t} - r_t \left(1 - \frac{b_t}{p_t}\right) - \frac{b_t}{p_t} r_t^m - \delta - r_t \frac{\Phi^{\text{new}}(h^{\text{own}})}{p_t}. \tag{14}$$

The first term in equation (14) 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.

[14] Returns to housing in the model are computed as $\log\left[\left(p_t^r + p_{t+1} - p_t\right)/p_t\right]$.

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

The second term in this expression is the expected real rate of housing appreciation. In our calibration, the average value of $E_t\left(p_{t+1}-p_t\right)/p_t$ is 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 (14) is the fixed cost of buying a house as a percentage of the house price. One difference between renting and buying not captured by equation (14) 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.

A number of observations follow from equation (14). 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 ($r_t\Phi^{\text{new}}(h^{\text{own}})/p_t$). 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:

$$r_t+\frac{b_t}{p_t}\left(r_t^m-r_t\right). \tag{15}$$

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 8. The model implies that home ownership rates rise as people get older. This result follows from 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 ($r_t\Phi^{\text{new}}(h^{\text{own}})/p_t$). Also, as income rises, people can afford bigger down payments on those homes, which 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.

From Figure 8, 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 8 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 7.9 percent. So, taking sampling uncertainty into account, the model does a good job of accounting for the average refinancing rate. The model is also consistent with the fraction of new mortgages issued in each period.[16] This fraction is 25 percent both in the model and the data.

Figure 9 plots the cumulative distribution function of refinanced loans 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 9 displays these fractions.

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. Every period a new cohort of households enters the economy. New households are randomly assigned to being homeowners or renters in a way that is consistent with the initial asset distribution. The mortgage rates of home owners in the new cohorts are drawn from the distribution of new mortgage rates in the data at every point in time. 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 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 the estimated version of equation (13). 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 9, the model does reasonably well at accounting for the data.

Andersen et al. (2015) and the references therein show that some people do not refinance their fixed-rate mortgage when market rates fall below their locked-in mortgage

[16] New mortgages include refinancing of existing mortgages and mortgages issued to people who buy a new home. This pool of people includes people who were renters, new cohorts who enter the housing market, and people who upgrade or downgrade the size of their house.

rate. This phenomenon is more pronounced at the top end of the interest rate gap. We could account for this "burnout" phenomenon by introducing heterogeneity in refinancing costs. However, this additional complexity is unlikely to change the model's implications for the state-dependent impact of monetary policy. The reason is that relatively few loans in our sample exhibit the burnout phenomenon. For example, the fraction of initial mortgages that are never prepaid is 0.3 percent.

We conclude by presenting time-series evidence on the model's implications for refinancing activity. The blue line in Figure 10 displays the fraction of loans that were refinanced in the U.S. between 1998 and 2007. The dashed line displays the analogue model time series. The model does reasonably well at capturing the broad movements in the time series, such as the run up in refinancing until 2004 which is associated with large declines in mortgage rates. The model also captures the subsequent decline in refinancing activity. The correlation between the data and model-implied paths is 80 percent.

7.3 State dependency of refinancing decisions

We now assess the ability of the model to account for the state-dependent nature of the effects of monetary policy on refinancing decisions. Using data simulated from the model, we estimate the following regression using the monetary policy shock as an instrument:

$$\rho_{t+4} = \beta_0 + \beta_1 \Delta R_t^M + \beta_2 \Delta R_t^M \times A_{t-1} + \beta_3 A_{t-1} + \eta_t. \tag{16}$$

This equation is a version of regression (2) without county fixed effects.[17] The variable ρ_{t+4} is the fraction of mortgages refinanced in the economy between quarters t and $t+4$. Table 7, panel A reports the model-based and data-based estimates of β_1 and β_2. The data estimates are reproduced from panel A of Table 2. The model does quite well at accounting for β_2 which governs the state dependent impact of a monetary policy

[17] To make the model regressions comparable with the data regressions we include a one-year lag of the refinancing rate.

shock. At the same time, the model somewhat overstates β_1, which governs the direct impact of interest rates on refinancing rates.

Another way to assess the implications of the model is to calculate the effect of a 50 basis points reduction in the mortgage rate on the refinancing rate at each point in time. Our results are displayed in Figure 4 along with the regression-based estimates of these effects. Taking sampling uncertainty into account, the model does reasonably well at tracking the regression-based estimates. Even in periods where the model does less well, its implications are only a few basis points outside the confidence interval.

We also compute the time series of four cross-sectional moments for the interest rate gap in the data and the model: the top 25 percentile, the median, the mean, and the bottom 25 percentile. The time-series correlation between these moments in the model and the data is 80 percent, 70 percent, 73 percent, and 90 percent, respectively.

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 run a version of regression (2) on data simulated from the model. The dependent variable is the fraction of new mortgages used to purchase a new home relative to the number of outstanding mortgages. Table 7, panel C reports our results. Both regression coefficients are statistically significant at the one-percent level. Also, 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 7 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. Then, a 25 basis points drop in mortgage rates raises the fraction of loans for new purchases to 6.1 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 7, 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 the state dependency of new home purchases.

7.5 Endogenous versus exogenous sources of state dependency

Our model implies a non-linear representation of the data which involves state dependency. So, our theory compels us to estimate a VAR that allows for state dependency. The VAR which we use to compute agents' expectations is an exogenous source of state dependency. But the model embodies other strong, endogenous sources of state dependency. The most important of these sources is the presence of fixed costs of refinancing or getting a mortgage for a new home.

To substantiate these claims, we shut down the exogenous state-dependence in the VAR by setting the relevant coefficients to zero. We then re-solve the model using the resulting linear VAR and re-calculate the statistics reported in Table 7. The results are reported in column 3 of that Table. Consider the regression results for the fraction of loans that are refinanced. From panel A, we see that the coefficient on the interaction term ($\Delta R_t \times$ Average Rate Gap) declines by roughly 33 percent. So, 33 percent of the state dependence comes from the VAR and two thirds is generated endogenously by the model. Roughly similar results hold for the fraction of loans that are cash-refinanced (panel B) and the fraction of loans for home purchases (panel C). Taken together these results demonstrate that it is quantitatively important to allow for state dependency in the VAR. At the same time, most of the state dependency is endogenously generated by the structural model.

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 model-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}):

$$c_{jt+1} - c_{jt} = \beta_{j0} + \beta_1 \Delta R_t^M + \beta_2 \Delta R_t^M \times A_{t-1} + \beta_3 A_{t-1} + \eta_t^c. \tag{17}$$

The coefficients in this regression are estimated using the monetary shocks as instruments. Table 8 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 1.43 percent. The direct effect ($\beta_1 \Delta R_t^M$) is 0.97 percent. The state dependent effect ($\beta_2 \Delta R_t^M \times$ average interest-rate gap) is 0.46 percent.[18]

To understand the mechanisms that underlie these effects, we estimate regression (17) 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. Forty eight percent of households are, 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

[18] Very little of the consumption response to mortgage rate changes is driven by the associated changes in house prices. We establish 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.

on consumption of an exogenous change in mortgage rates is 4.6 and 0.78 percent for constrained and unconstrained households, respectively. So, the consumption response is predominantly driven by the constrained households.

Roughly 84 percent of the households who refinance engage in cash-out refinancing. This value is in line with the evidence presented by Chen, Michaux, and Roussanov (2020). 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 19.2 percent. This effect is broadly consistent with the empirical estimates of Bhutta and Keys (2016).[19]

To assess the model's implications for the state-dependent nature of cash-out refinancing, we use model-simulated data to estimate a version of regression (16) using monetary policy shocks as instruments. Here, the dependent variable is the fraction of total loans with cash-out refinancing. Our results are reported in Table 7, panel B. Comparing columns II in panels A and B, we see that in the data the state-dependent effect of an interest rate cut on refinancing and cash-out refinancing is about the same. The model captures, qualitatively, the state-dependent nature of cash-out refinancing, i.e. the larger are potential savings, the larger is the response of cash-out refinancing to an interest rate cut.

Our model abstracts 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

[19] 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 23 percent.

effect on the consumption of constrained households.[20] 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 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.

It is possible that lenders respond to a fall in their income by reducing the flow of credit to borrowers. The precise way in which interest rates and the quantity of credit change adjust depends on monetary policy, the nature of financial frictions and whether the economy is open or closed. For example, in an open economy like the U.S., international capital flows could adjust to compensate for any decline in the flow of credit from domestic lenders to domestic borrowers.

Finally, we do not explicitly model the wealth effects of duration risk on mortgage investors. This risk is embedded in the mortgage rates that we use to estimate equation (7). In solving the model, the mortgage rate that people face and their expectations of future mortgage rates reflect changes in the duration-risk premia arising from the state of the economy. So, even though we don't explain those premia, we do account for them when solving the model.

8.1.1 The importance of life-cycle dynamics

Life-cycle dynamics play an important role in our quantitative results. To illustrate this role, we consider an alternative version of the model with no income life-cycle dynamics. Unlike in our benchmark model, young people have no systematic incentive to borrow against future income. As a result, mortgage balances are smaller and fewer people are financially constrained. So, the gains from refinancing are smaller.

[20]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 this alternative economy, both the direct and state-dependent effect of monetary policy on refinancing are smaller. The direct effect of a change in mortgage rates as measured by β_1 (the coefficient on ΔR_t^M in equation (2)) drops from 0.06 in the benchmark model to roughly zero. The state dependent effect as measured by β_2 (the coefficient on $\Delta R_t^M \times$ average interest-rate gap in equation (2)) drops from 0.232 to 0.081. We obtain similar results for the fraction of loans that are cash-out refinanced.

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.

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 11. 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 (13). 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 four. In period five, 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 18 percent of people refinance in the impact period of the shock and aggregate consumption increases 1.7 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 four. The central bank then cuts the interest rate by 50 basis points in period five. From row (ii) of Table 9, Panel A we see that only 7 percent of households refinance in the impact period of the shock and there is only a 0.2 percent rise in consumption. The reason for these small effects is that only 23 percent of people face a positive interest-rate gap in period five. 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 four. The central bank then cuts interest rates by 50 basis points in period five. From row (ii) of Table 9, Panel B we see that in this scenario, 12 percent of people refinance in the impact period of the shock and there is a 0.6 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.[21]

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.

[21]The average interest rate is a key determinant of when households refinance. When they do so, it is often optimal to take advantage of the new loan and cash out. Because of the fixed costs of refinancing, it is not in general optimal to refinance just to cash out.

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 Figure 12. 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 0.8, 1.1 and 1.9 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 1.7 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.[22]

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

[22]The results of this experiment are not driven by the model's low burnout rate. We could match the empirical burnout rate by adding large refinancing costs for a subset of the population. But if people with high refinancing costs did not refinance between periods 2 and 10, they would be unlikely to refinance in period 11 through 14.

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 after a series of interest declines. To illustrate this point, suppose that starting from steady state, the interest rate falls from 3.5 percent to 1 percent and stays at 1 percent between periods two and six.[23] Then, in period seven, the interest rate falls by an additional 50 basis points (not shown on the Figure). According to our model, only 5 percent of people refinance in the impact period of the shock and there is only a 0.5 percent rise in consumption. These modest effects contrast sharply with the effect of an interest rate fall in the benchmark scenario where 16 percent of people refinance in the impact period of the shock and there is a 1.7 percent rise in consumption. The intuition for this result is the same as the one underlying Panel B of Table 9. In this exercise, most people already have low mortgage rates either because they refinanced an existing mortgage or purchased a new home. Either way, the stock of people with a large, positive interest rate gap is small. For this reason, a further interest rate cut has a small impact on refinancing and 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 1.7 percent rise in consumption. Suppose instead that the interest rate fell by 100 basis points. Then consumption would rise by 2.9 percent. This increase is roughly the same if, starting from steady state, the interest rate falls by 100 basis.

[23]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 (13).

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 as long as monetary policy is not constrained by the effective lower bound (ELB).

There is considerable debate about the importance of the ELB. For example, Debortoli, Gali, and Gambetti (2020) argue that the ELB was not a binding constraint in the aftermath of the financial crises. The conventional view (e.g. Eggertsson (2003), Eggertsson and Woodford (2004), and Christiano, Eichenbaum and Rebelo (2011)) is that the ELB does constrain monetary policy. Swanson and Williams (2014) argue that the ELB was not binding before 2011 but did constrain monetary policy thereafter. Kiley and Roberts (2017) argue that the ELB will be binding 30 to 40 percent of the time in the future. To the extent that the ELB is a constraint on monetary policy, it would be difficult for the Fed to lower rates by large amounts after a prolonged period of low interest rates.

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 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?

10 References

Agarwal, Sumit, John Driscoll, and David Laibson, 2013, "Optimal Mortgage Refinancing: A Closed Form Solution," *Journal of Money, Credit, and Banking* 45, 591—622.

Andersen, S., Campbell J., Nielsen K., and Ramadorai T. "Inattention and Inertia in Household Finance: Evidence from the Danish Mortgage Market," National Bureau of Economic Research working paper No. 21386, 2015.

Auclert, Adrien "Monetary Policy and the Redistribution Channel," manuscript, Stanford University, 2017.

Bailey, Michael, Cao, Rachel, Kuchler, Theresa, Stroebel, Johannes, and Wong, Arlene. Replication data for: "Social Connectedness: Measurement, Determinants, and Effects." *American Economic Association*, 2018. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2019-10-12. https://doi.org/10.3886/E114016V1

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra "Regional Heterogeneity and the Refinancing Channel of Monetary Policy," *Quarterly Journal of Economics*, 2018.

Berger, David and Joseph Vavra, "Consumption Dynamics During Recessions," *Econometrica*, 2015, 83 (1), 101—154.

Berger, David, Guerrieri, Veronica, Lorenzoni, Guido and Vavra, Joseph, 2017. "House Prices and Consumer Spending." *The Review of Economic Studies*, 85(3), pp.1502-1542.

Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra (2018), "Mortgage Prepayment and Path-Dependent Effects of Monetary Policy," manuscript, Northwestern University.

Bhutta, Neil and Benjamin J. Keys. 2016. "Interest Rates and Equity Extraction during the Housing Boom." *American Economic Review* 106 (7):1742–1774.

Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [DFF], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/I 2021.

Board of Governors of the Federal Reserve System (US), 3-Month Treasury Bill Secondary Market Rate [TB3MS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TB3MS, 2021.

Chen, Hui, Michael Michaux, and Nikolai Roussanov. "Houses as ATMs: Mortgage Refinancing and Macroeconomic Uncertainty," *The Journal of Finance* 75, no. 1 (2020): 323-375.

Christiano, Lawrence, Martin Eichenbaum, and Sergio Rebelo. "When is the Government Spending Multiplier Large?" *Journal of Political Economy* 119, no. 1 (2011): 78-121.

Cochrane, John H., and Monika Piazzesi. "The Fed and Interest rates-a High-frequency Identification." *American Economic Review* 92, no. 2 (2002): 90-95.

Corelogic Loan-Level Analytics Mortgage Data and Corelogic Origination data, accessed 2018/01/22.

Debortoli, Davide, Jordi Gali, and Luca Gambetti. "On the Empirical (Ir) relevance of the Zero Lower Bound Constraint," *NBER Macroeconomics Annual* 34, no. 1 (2020): 141-170.

DeFusco, Anthony A. and John Mondragon "No Job, No Money, No Refi: Frictions to Refinancing in a Recession," manuscript, Northwestern University, 2018.

De Nardi, Mariacristina and Fang Yang "Bequests and Heterogeneity in Retirement Wealth," *European Economic Review*, Elsevier, vol. 72(C), pages 182-196, 2014.

Di Maggio, Marco, Amir Kermani, Benjamin J. Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao "Interest Rate Pass-through: Mortgage rates, Household Consumption, and Voluntary Deleveraging," *American Economic Review* 107, no. 11 (2017): 3550-88.

Diaz, Antonia, and J. Luengo-Prado, Maria. 2012. “The User Cost, Home Ownership and Housing Prices: Theory and Evidence from the US,” International Encyclopedia of Housing and Home, 228-234.

Diaz, Antonia and Maria J. Luengo-Prado “The User Cost, Home Ownership and Housing Prices: Theory and Evidence from the U.S.” in Smith, S.J.; Elsinga, M.; Fox-O'Mahony, L.; Ong, S.E.; Wachter, S. (editors) *The International Encyclopedia of Housing and Home*, Elsevier (2012).

Diep, Peter, Andrea L. Eisfeldt, Scott Richardson, 2017, “Prepayment Risk and Expected MBS Returns,” NBER Working Paper No. 22851

Doepke, Matthias, and Martin Schneider. “Inflation and the Redistribution of Nominal Wealth.” *Journal of Political Economy* 114, no. 6 (2006): 1069-1097.

Doepke, Matthias, Martin Schneider, and Veronika Selezneva. ”Distributional Effects of Monetary Policy,” manuscript, Northwestern University, 2018.

Dunn, Kenneth B., and John J. McConnell. “Valuation of GNMA Mortgage-backed Securities,” *The Journal of Finance* 36, no. 3 (1981): 599-616.

Eggertsson, Gauti B. “Zero Bound on Interest Rates and Optimal Monetary Policy,” *Brookings papers on economic activity* 2003, no. 1 (2003): 139-233.

Eggertsson, Gauti B., and Michael Woodford. “Policy Options in a Liquidity Trap,” *American Economic Review* 94, no. 2 (2004): 76-79.

Federal Reserve Bank of Cleveland, 30-year expected inflation. https://www.clevelandfed.org/our-research/indicators-and-data/inflation-expectations.aspx., 2021.

Federal Reserve Bank of Philadelphia. 2021. “Survey of Professional Forecasters.”

Freddie Mac Single Family Loan-Level Dataset and Quarterly Refinance Report.

Garriga, C. and Hedlund, A., 2017. Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession. FRB St. Louis Working Paper, (2017-30).

Garriga, Carlos, Finn E. Kydland, and Roman Sustek. “Mortgages and monetary policy.” *The Review of Financial Studies* 30, no. 10 (2017): 3337-3375.

Gertler, Mark, and Peter Karadi. “Monetary Policy Surprises, Credit Costs, and

Economic Activity." *American Economic Journal: Macroeconomics* 7.1 (2015): 44-76.

Gilchrist, Simon, David López-Salido, and Egon Zakrajek. "Monetary Policy and Real Borrowing Costs at the Zero Lower Bound," *American Economic Journal: Macroeconomics* 7, no. 1 (2015): 77-109.

Global Financial Data Real Estate database.

Gorodnichenko, Yuriy, and Michael Weber "Are Sticky Prices Costly? Evidence from the Stock Market.," *American Economic Review* 106, no. 1 (2016): 165-99.

Green, Jerry, and John B. Shoven. 1986. "The Effects of Interest Rates on Mortgage Prepayments," *Journal of Money, Credit and Banking* 18, no. 1: 41-59.

Greenwald, Daniel "The Mortgage Credit Channel of Macroeconomic Transmission," manuscript, Sloan School of Management, MIT, 2016.

Guren, A.M., Krishnamurthy, A. and McQuade, T.J., 2018. "Mortgage Design in an Equilibrium Model of the Housing Market " (No. w24446). National Bureau of Economic Research.

Guren, A.M., McKay, A., Nakamura, E. and Steinsson, J., 2018. "Housing Wealth Effects: The Long View " (No. w24729). National Bureau of Economic Research.

Gürkaynak, Refet S., Brian Sack, and Eric Swanson. "The Sensitivity of Long-term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models." *American Economic Review* 95, no. 1 (2005): 425-436.

Guvenen, Fatih, and Anthony A. Smith. 2014. "Inferring Labor Income Risk and Partial Insurance from Economic Choices." *Econometrica*, 82(6): 2085–2129.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song. 2015. "What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?" National Bureau of Economic Research Working Paper 20913.

Huggett, Mark, "Wealth Distribution in Life-cycle Economies", *Journal of Monetary Economics*, Volume 38, Issue 3, December 1996, Pages 469-494.

Hurst, Erik, Keys, Benjamin, Seru, Amit and Vavra, Joseph, "Regional Redistribution Through the U.S. Mortgage Market," *American Economic Review*, 2016, 106(10), 2982-3028.

Iacoviello, M., 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. *American Economic Review*, 95(3), pp.739-764.

Iacoviello, M. and Pavan, M., 2013. Housing and Debt over the Life Cycle and Over the Business Cycle. *Journal of Monetary Economics*, 60(2), pp.221-238.

Khandani, Amir E., Andrew W. Lo, and Robert C. Merton, 2013, "Systemic Risk and the Refinancing Ratchet Effect", *Journal of Financial Economics* 108, 29-45.

Kaplan, Greg, Kurt Mitman and Giovanni L. Violante "The Housing Boom and Bust: Model Meets Evidence," manuscript, Princeton University, 2017.

Kaplan, Greg, Benjamin Moll and Gianluca Violante "Monetary Policy According to HANK," *American Economic Review*, 108(3), 697-743, 2018.

Kaplan, Greg and Giovanni L. Violante & Justin Weidner, 2014. "The Wealthy Hand-to-Mouth," *Brookings Papers on Economic Activity*, vol 2014(1), pages 77-138.

Kiley, Michael T., and John M. Roberts. " Monetary Policy in a Low Interest Rate World."*Brookings Papers on Economic Activity* 2017, no. 1 (2017): 317-396.

Kuttner, Kenneth N. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics* 47, no. 3 (2001): 523-544.

LaCour-Little, Michael. "The Evolving Role of Technology in Mortgage Finance." *Journal of Housing Research* (2000): 173-205.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider. 2015. "The Housing Market(s) of San Diego." *American Economic Review*, 105(4): 1371-1407.

Mack, A., and E. Martínez-García. 2011. "A Cross-Country Quarterly Database of Real House Prices: A Methodological Note." Globalization and Monetary Policy Institute Working Paper No. 99, Federal Reserve Bank of Dallas.

McKay, A., Nakamura, E. and Steinsson, J., 2016. "The Power of Forward Guidance Revisited," *American Economic Review*, 106(10), pp.3133-58.

Mian Atif, Kamelesh Rao and Amir Sufi "Household Balance Sheets, Consumption, and the Economic Slump" *Quarterly Journal of Economics*, 2013, 1687-1726

Mian, Atif, and Amir Sufi. 2014. "House Price Gains and U.S. Household Spending from 2002 to 2006." National Bureau of Economic Research, Inc NBER Working Papers 20152.

Nakamura, Emi and Jón Steinsson "High Frequency Identification of Monetary Non-Neutrality: The Information Effect. " *Quarterly Journal of Economics*, 133(3), 1283-1330, August 2018.

OECD. 2021, Housing prices (indicator). doi: 10.1787/63008438-en

Piazzesi, M. and M. Schneider (2016): "Housing and Macroeconomics," *Handbook of Macroeconomics*, 2, 1547–1640.

Rios-Rull, J.V. and Sanchez-Marcos, V., 2008 "An Aggregate Economy with Different Size Houses," *Journal of the European Economic Association*, 6(2-3), pp.705-714.

Rouwenhorst, Geert K., "Asset Pricing Implications of Equilibrium Business Cycle Models," in Thomas Cooley, ed., *Structural Models of Wage and Employment Dynamics*, Princeton: Princeton University Press, 1995.

Scharfstein, David and Adi Sunderam, "Market Power in Mortgage Lending and the Transmission of Monetary Policy," 2013 NBER working paper 19156.

Schwartz, Eduardo S. and Walter N. Torous 1989. "Prepayment and the Valuation of Mortgage-Backed Securities." *Journal of Finance* 44(2), pp. 375-392.

Stock, James H., and Motohiro Yogo. 2005. Testing for Weak Instruments in Linear IV regression. In Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg, ed. D. W. K. Andrews and J. H. Stock, 80–108. New York: Cambridge University Press.

Swanson, Eric T., and John C. Williams. "Measuring the Effect of the Zero Lower Bound on Medium-and Longer-Term Interest Rates." *American Economic Review* 104, no. 10 (2014): 3154-85.

U.S. Bureau of Labor Statistics, Local Area Unemployment Statistics, Unemployment rate, not seasonally adjusted.

U.S. Bureau of Economic Analysis, Personal Income, Population, Per Capita Personal Income, and Per capita personal income.

U.S. Bureau of Economic Analysis, Real Disposable Personal Income: Per Capita [A229RX0Q048SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A229RX0Q048SBEA, 2021.

U.S. Board of Governors of the Federal Reserve System, "Survey of Consumer Finances", https://www.federalreserve.gov/econres/scfindex.htm., 2021.

U.S. Census Bureau. 2016. "Building Permits Survey."

Woodford, M., 2012 "Methods of Policy Accommodation at the Interest-rate Lower Bound." In *Proceedings-Economic Policy Symposium-Jackson Hole* (pp. 185-288). Federal Reserve Bank of Kansas City.

Wong, Arlene. 2020 "Population Aging and the Transmission of Monetary Policy to Consumption," manuscript, Princeton University.

Tables and Figures

Table 1: First-stage estimates

First stage y-variable:	ΔR(t) (I)	ΔR(t) x A(t-1) (II)
Ɛ(t)	0.613***	0.197***
	(0.006)	(0.007)
Ɛ(t) x Average rate gap	0.135***	0.109***
	(0.009)	(0.011)
F-statistic	4,511	434

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 2: State dependency of monetary policy and refinancing

	(I)
Panel A: Fraction refinanced	
ΔR(t)	0.040
	(0.023)
ΔR(t) x Average rate gap	0.266***
	(0.076)
Panel B: Fraction cash-out refinanced	
ΔR(t)	0.074***
	(0.007)
ΔR(t) x Average rate gap	0.176***
	(0.027)
Panel C: Change in balance, given cash-out refinance	
ΔR(t)	0.237***
	(0.026)
ΔR(t) x Average rate gap	0.215*
	(0.132)
County Fixed Effects	Yes
SPF Controls	Yes
Additional county controls	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 3: State dependency of monetary policy, unemployment and housing permits

	Change in unemployment rate over the year	**Housing permit growth over the year**
	(I)	**(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 4: Model parameter values

Parameters		Value
σ	Intertemporal elasticity of substitution	0.5
δ	Housing depreciation rate	3%
ϕ	Collateral constraint	0.2
Φ^{new}	Fixed cost of buying a house	1,100.00
Φ^{new}	Variable cost of buying a house (% of house price)	4
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
ϕ^{refi}	Transaction cost of refinancing	2,100

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

Table 5: 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
	(14.090)	(0.119)
log r_t	0.334	-0.002
	(0.069)	(0.001)
log p_t		-0.022
		(0.014)
constant	-0.030	3.187
	(0.020)	(0.488)

Notes: Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels. These are the estimated coefficients for equations (8) and (9). See text for more detail.

Table 6: Estimated Aggregate Process

	Regression with dependent variable			
Variables	log y_t	log r_t	log p_t	log savings$_t$
log y_{t-1}	-0.297	13.520	-0.019	-3.486
	(0.108)	(2.845)	(0.047)	(2.365)
log r_{t-1}	0.000	0.612	0.010	0.223
	(0.002)	(0.051)	(0.002)	(0.147)
log p_{t-1}	0.131	2.461	0.810	0.928
	(0.075)	(2.114)	(0.070)	(1.710)
log savings$_{t-1}$	-0.009	0.157	-0.030	-0.529
	(0.006)	(0.142)	(0.008)	(0.296)
log savings$_{t-1}$ x log r_{t-1}	-0.002	0.133	-0.009	-0.189
	(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 7: State dependency of monetary policy and refinancing: Model vs Data

	Data	Model	
		Benchmark	No state-dependency in VAR
Panel A: Fraction of loans that refinanced			
ΔR(t)	0.040	0.097	0.102
	(0.023)		
ΔR(t) x Average rate gap	0.266***	0.209	0.136
	(0.076)		
Panel B: Fraction of loans that are cash-out refi			
ΔR(t)	0.074***	0.098	0.104
	(0.007)		
ΔR(t) x Average rate gap	0.176***	0.211	0.137
	(0.027)		
Panel C: Fraction of loans for home purchases			
ΔR(t)	0.095***	0.114	0.066
	(0.006)		
ΔR(t) x Average rate gap	0.115***	0.134	0.078
	***		

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 8: State dependency of monetary policy

Effect on refinancing:	
Overall effect of a 50 bp expansionary shock	5.23%
$\beta_1 \Delta R_t$	4.83%
$\beta_2 \Delta R_t$ times mean(φ_t)	0.40%
Effect on consumption:	
Overall effect of a 50 bp expansionary shock	1.43%
$\beta_1 \Delta R_t$	0.97%
$\beta_2 \Delta R_t$ times mean(φ_t)	0.46%

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.

Table 9: Alternative paths of monetary policy

Rate path prior to a 50bp cut	Average rate gap before cut	Fraction with positive rate gap	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%	18%	1.6%	0.68
(ii) Rising from 3.5% to 6.5% over 4 pds	-0.62%	23%	7%	0.2%	0.83
Difference (i)-(ii)	0.62%	77%	11%	1.4%	-0.15
Panel B: Effects of Flat vs Falling History					
(i) Flat at about 3.5%	0.00%	100%	18%	1.6%	0.68
(ii) Falling from 3.5% to 1% over 4 pds	0.45%	100%	12%	0.6%	0.66
Difference (i)-(ii)	-0.45%	0%	6%	1.0%	0.02

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

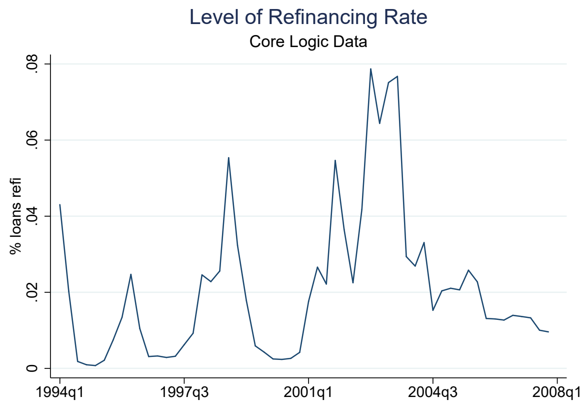
Table 10: Alternative paths of monetary policy

Rate path prior to a rate cut	Average rate gap before cut	Fraction with positive rate gap	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%	18%	1.6%	68%
(b) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **1 pd**	-0.48%	67%	10%	0.8%	56%
(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%	86%	14%	1.1%	66%
(d) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **3 pds**	-0.11%	88%	16%	1.9%	70%
Reloading Effect with 100bp cut					
(e) Benchmark case: continuously flat at 3.5% prior to a 100bp rate cut	0.00%	100%	19%	2.7%	72%
(f) 3.5% cut to 1% for 4 pds, rise for 3 pds to 3.5%, flat at 3.5% for **1 pd**	-0.48%	68%	18%	3.1%	56%

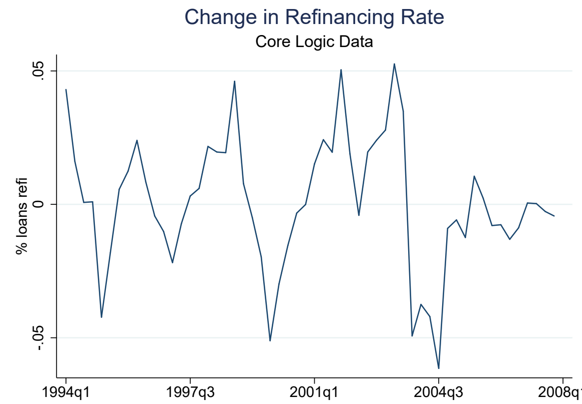
Notes: Alternative paths of monetary policy. See text for more detail.

Figure 1: Time Series of the Refinancing Rate

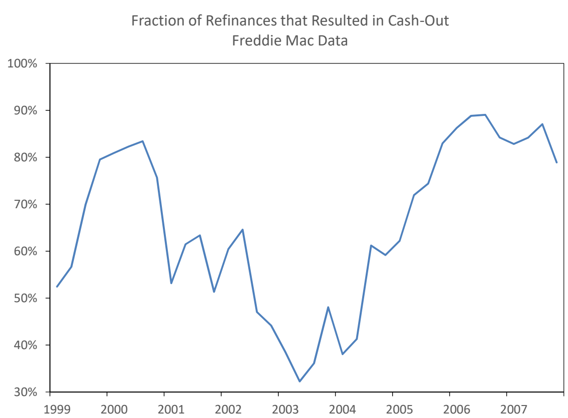
(a) Refinancing Rate



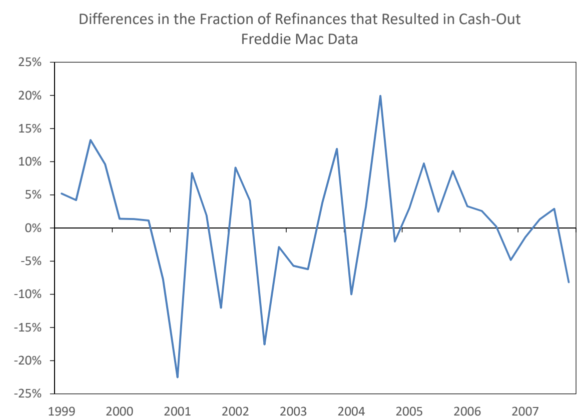
(b) Change in Refinancing Rate



(c) Share of Refinancing With Cash-Out

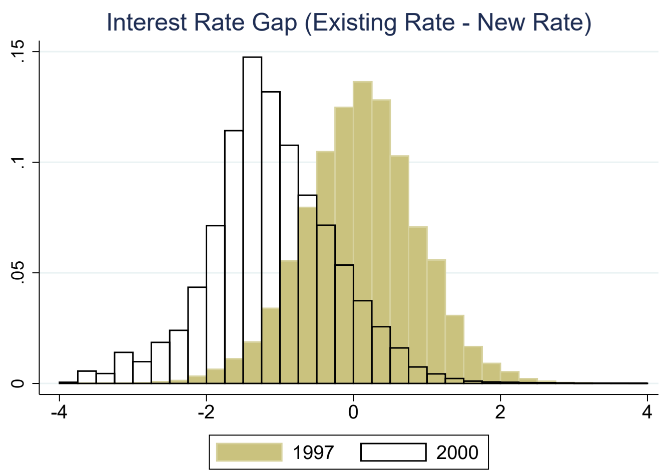


(d) Change in Share of Refi With Cash-Out



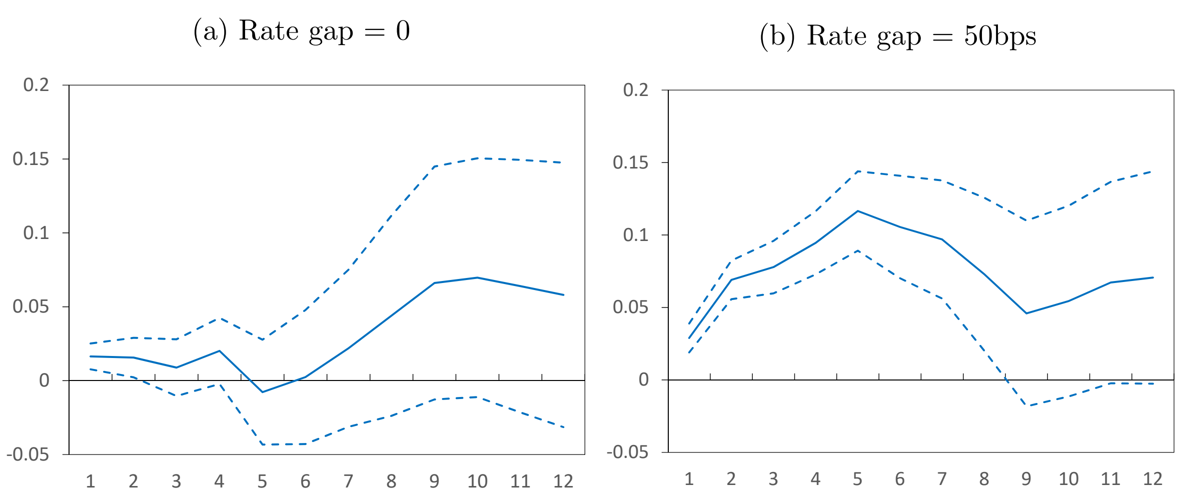
Notes: Panels (a) and (b) depicts the time series of the refinancing rate (fraction of loans that were refinanced in that quarter) and the quarterly change in the refinancing rate, respectively. Panels (c) and (d) depicts the time series of the share of refinanced loans that involved a balance increase (i.e. cash-out) and the quarterly change in this share, respectively.

Figure 2: 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 3: Cumulative Refinancing Rate in Response to a 50bp Mortgage Rate Cut



Notes: The figure depicts the cumulative response function of refinancing to a 50 bp decline in mortgage rates. Panel A shows the response if the initial average rate gap is zero. Panel B shows the response if the initial average rate gap is instead 50 basis points.

Figure 4: Effect on the Refinancing Rate of a 50bp cut, at each point in time

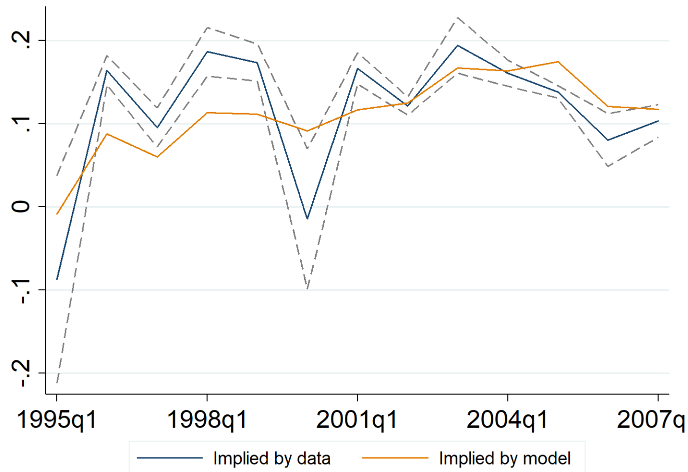
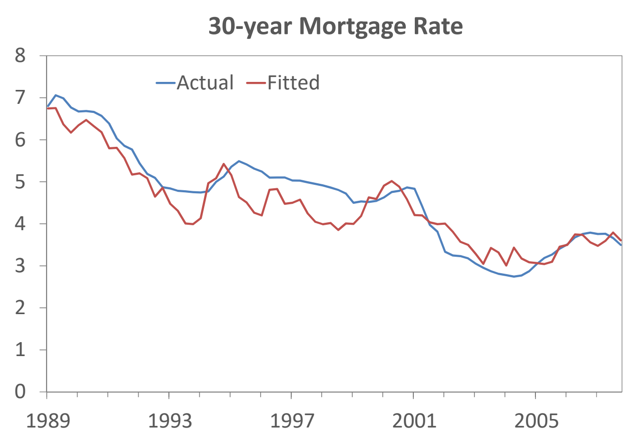
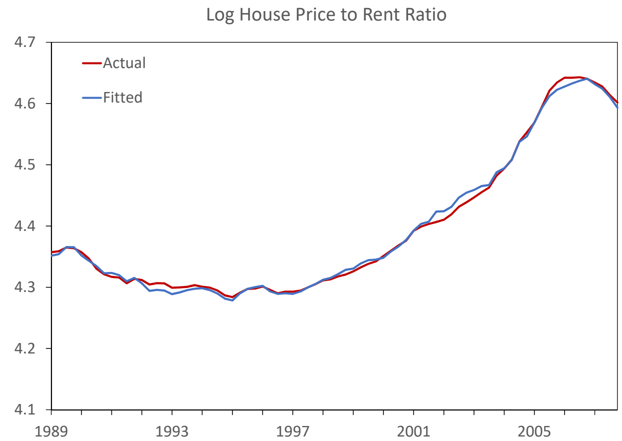


Figure 5: Time series of fitted and actual mortgage rates



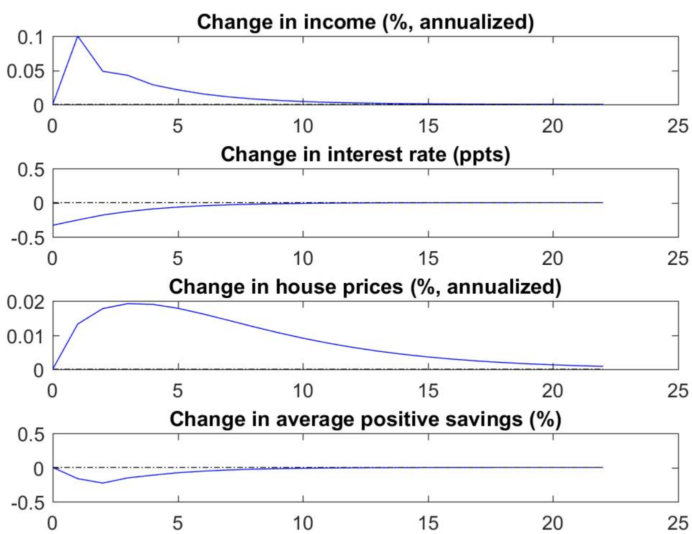
Notes: The figure depicts the fitted and actual mortgage rate data. See text for more details.

Figure 6: Time series of fitted and actual house price to rent ratios



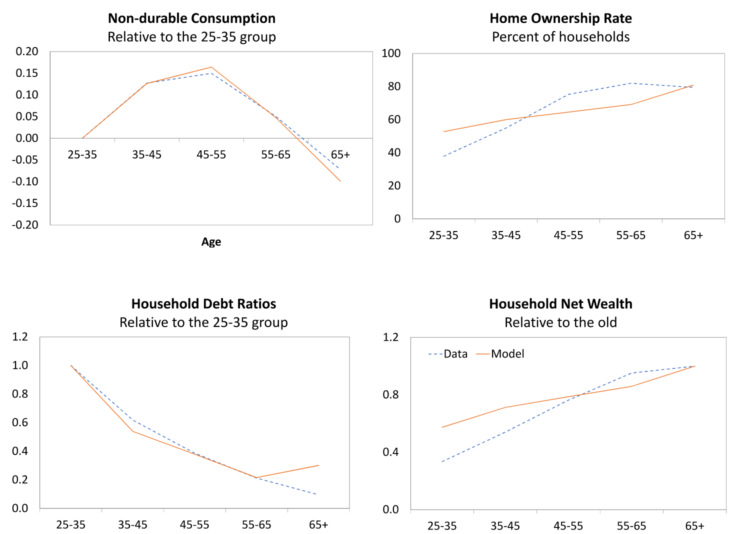
Notes: The figure depicts the fitted and actual house price to rental ratios. See text for more details.

Figure 7: Impulse response function of aggregate variables



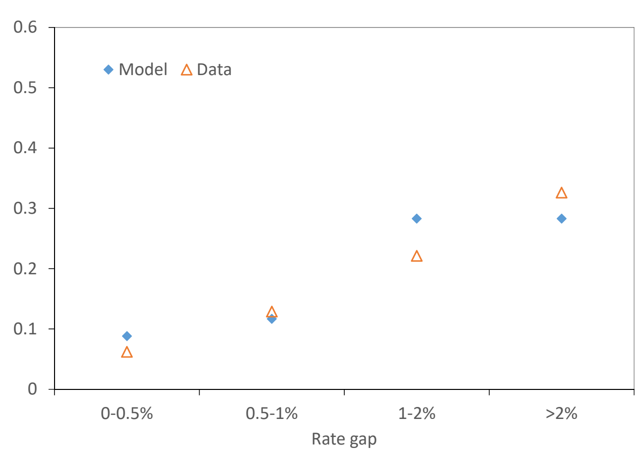
Notes: The figure depicts the impulse response function to a 1 sd interest rate shock. See text for details.

Figure 8: Life-cycle moments



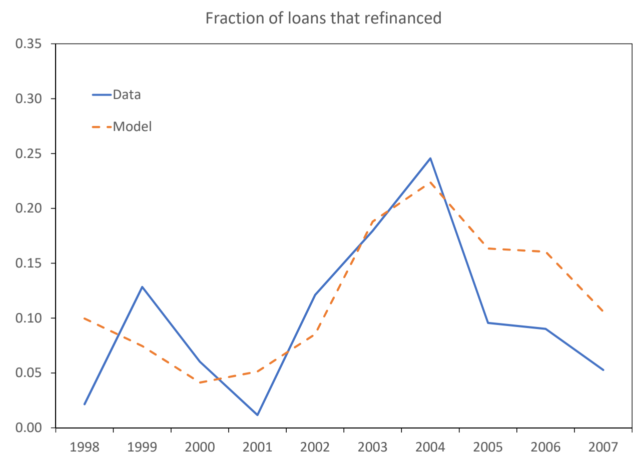
Notes: The figure depicts the fitted and actual life-cycle moments. See text for more details.

Figure 9: Refinancing, given the interest-rate gap



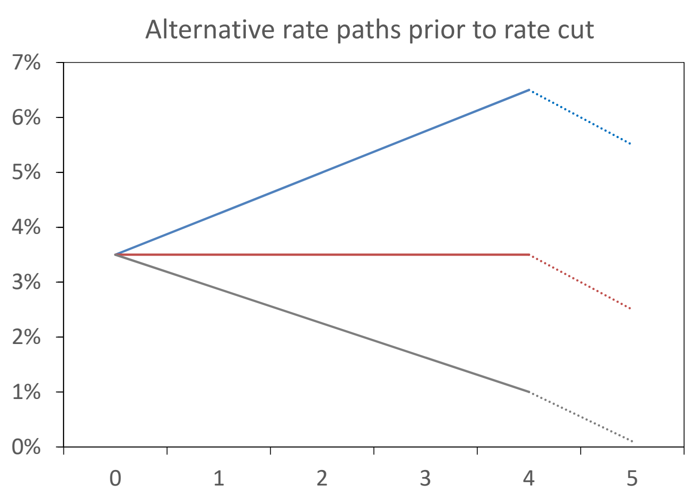
Notes: The figure depicts propensity to refinance for each given interest-rate gap in the data and the model. See text for more details.

Figure 10: Time Series of Refinancing



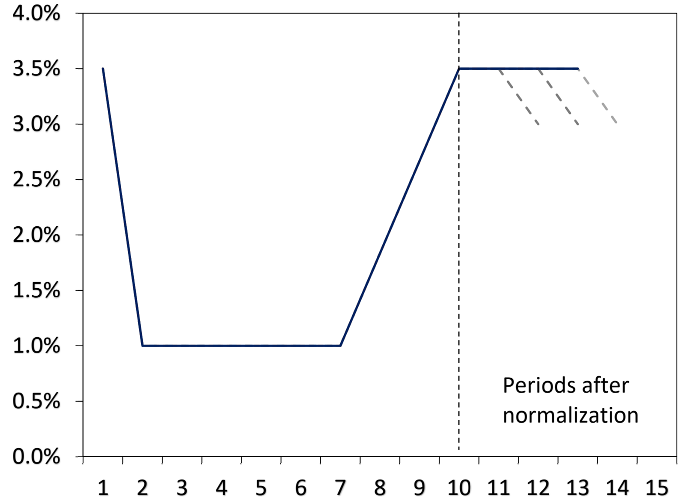
Notes: The figure depicts propensity to refinance over time in the data and the model. See text for more details.

Figure 11: Alternative interest rate paths



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

Figure 12: Alternative interest rate paths



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