State Dependent Effects of Monetary Policy: the Refinancing Channel *

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October 2018

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. Motivated by the rapid expansion of Fintech, we study the impact of a fall in refinancing costs on the efficacy of monetary policy. Our model implies that as refinancing costs decline, the effects of monetary policy become less state dependent and more powerful.

Keywords: monetary policy, state dependency, refinancing.

JEL codes: E52, G21

*We thank Adrien Auclert, Martin Beraja, David Berger, Luigi Bocola, Monika Piazzesi, Martin Schneider, and Joe Vavra for their comments.

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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. The key empirical properties of the model are as follows. 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.

Our model implies that the effect of a given interest rate cut depends on the history of monetary policy choices. A given interest rate cut is less powerful when proceeded by a sequence of rate hikes. When rates have been rising, many home owners have existing fixed mortgage rates lower than the current market rate. So these home owners are not motivated to refinance in response to a modest fall in the interest rate. A given interest rate cut is more powerful when proceeded by a sequence of rate cuts. When rates have been falling, many consumers have existing fixed mortgage rates higher than the current market rate. So these home owners are motivated to refinance in response to an interest rate cut.

We use our model to study how the efficacy of monetary policy and the state-dependency of its effects are affected by a decline in refinancing costs. This question is particularly important because of the growing share of Fintech lenders in mortgage

markets. Buchak et. al. (2017) show that the market share of these lenders has increased from 4 to 15 percent between 2007 and 2015. Fuster et. al. (2018) show that Fintech lenders substantially reduce the costs, broadly conceived, of refinancing. Strikingly, they find that in parts of the country where Fintech lenders have a greater presence, existing borrowers are more likely to refinance.

Our model implies that as refinancing costs decline, the effects of monetary policy become less state dependent. The intuition for this result is as follows. As refinancing costs decline, refinancing rates increase. This effect leads the distribution of savings from refinancing to vary less over time and to become more concentrated around zero. So, the effects of monetary policy become less state dependent.

The flip side of this result is that, as refinancing cost decline, monetary policy becomes more powerful. The intuition is as follows. In our model, many households face binding borrowing constraints. When refinancing costs decline, a given fall in interest rates induces more of these types of households to engage in cash-out refinancing, that is, their new mortgages are larger than the principal owed in the mortgages they refinance. These households use the additional resources to boost consumption. This transmission mechanism of monetary policy is consistent with a large empirical literature that dates back to at least Hurst and Stafford (2004) as well as more recent evidence from Ganong and Noel (2018).

The previous discussion about the implications of our model abstracts from the behavior of bank owners. If those owners have binding borrowing constraints 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. In fact, we think that bank owners are best characterized as being unconstrained. In our model, the consumption of unconstrained households responds by very little to a monetary policy shock. If bank owners are like these unconstrained households, they respond very little to a monetary policy shock. The response of aggregate consumption in our model comes mostly from what Kaplan, Violante and Weidner (2014) call hand-to-mouth households. These are

households whose liquid assets are less than two weeks of income.

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 points out various reasons for 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, with this literature, we focus on reasons why the efficacy of monetary policy depends on the state of the economy because of demand-side considerations, i.e. household's desire for refinancing. We certainly believe that supply-side constraints were very important in the aftermath of the financial crisis. But we also think that demand-side considerations were very important prior to the crisis and will become increasingly important as credit markets return to normal.

Our empirical results are closely related to contemporaneous, independent work by Berger, Milbradt, Tourre, and Vavra (2018). Both their paper and ours show that the effects of monetary policy are state dependent where the relevant state is the distribution of savings from refinancing.

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 use our model to study how the effects of monetary policy depend on the history of interest rates and the costs of refinancing. Section 8 provides some conclusions.

2 Related literature

Our paper relates to three strands of literature. The first strand is a large body of empirical work that studies consumption and refinancing responses to interest rate changes. This literature shows that households increase their expenditures when they reduce their mortgage payments and engage in cash-out activity (see, e.g. Mian, Rao and Sufi (2013), Chen, Michaux, and Roussanov (2013), Khandani, Lo, and Merton (2013), Bhutta and Keys (2016), Di Maggio et al. (2017), Agarwal et al. (2017), Abel and Fuster (2018), and Beraja et al. (2018)). In this paper, we extend the existing literature by showing that the effects of interest rate changes on refinancing and real outcomes depends on the distribution of mortgage rates. This type of state dependency differs from the state dependency based on loan-to-valuation constraints or home equity emphasized by Beraja et al (2018).

The second strand of literature focuses on the role of the mortgage market in the transmission of monetary policy. Garriga, Kydland and Sustek (2017) and Greenwald (2016) model the transmission mechanism using a representative borrower and saver model. In contrast, we use an heterogenous agent, life-cycle model that features transactions costs and borrowing constraints. Our model is most closely related to Guren, Krishnamurthy, and McQuade (2017), Hedlund et al. (2017), Wong (2018), Kaplan, Violante and Mittman (2017), Auclert (2017) and Kaplan, Violante and Moll (2018). In contrast to these papers, we focus on the state-dependent effects of monetary policy, and how these effects are shaped by past interest rate decisions made by the Federal Reserve.

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

3 Data

Our empirical work is primarily based on Core Logic Loan-level Market Analytics, a loan-level panel data set with observations beginning in 1993. These data include borrower characteristics (e.g. FICO and ZIP code) and loan-level information.[1] The latter includes the principal of the loan, the mortgage rate, the loan-to-value ratio (LTV), and the purpose of the loan (whether it refinances an existing loan or finances the purchase of a new house).

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

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

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

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

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

on a variety of factors, including the old and new mortgage interest rates, outstanding balances and the precise refinancing strategy that a household pursues. In general, it is not possible to construct a simple, non-parametric summary statistic of these potential savings. We consider two measures of potential savings, which we discuss below. These measures are variants of those used in a large literature that studies prepayment risk (see, e.g. Gabaix, Krishnamurthy, and Chernov (2007), Diep, Eisfeldt, and Richardson (2017), and Dunn, and Longstaff (2018)).

The average interest-rate gap. Our first measure of potential savings from refinancing is based on the difference between the current and the alternative mortgage rate that the household i could refinance at. We compute the average of time-t interest-rate gaps between new and old loan as:

$$A_{1t} = \frac{1}{n_t} \sum_{i=1}^{n_t} \left[r_{it}^{\text{old}} - r\left(\text{FICO}, \text{region}\right)_{it}^{\text{new}} \right]. \tag{1}$$

Here, $r\left(\text{FICO}, \text{region}\right)_{it}^{\text{new}}$ is the interest rate at time t for a new 30-year conforming mortgage for the same FICO and region as the original mortgage. We group FICO scores into the following bins: below 600, $600-620$, $620-640$,... ,...,$760-780$, greater than 780. The variable n_t denotes the number of mortgages outstanding at time t. We refer to A_{1t} as the average interest-rate gap. This gap is a real variable, since it is based on the difference between two nominal interest rates. The annualized unconditional quarterly mean and standard deviation of A_{1t} is -14 basis points and 70 basis points, respectively. We condition on region to capture the possibility that mortgage rates vary by region, say because of differences in income or house price growth.[2] We also considered versions of $r(.)_{it}^{\text{new}}$ that condition in a non-parametric way on additional variables like the loan-to-valuation ratio or the mortgage balance. Adding these measures did

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

not significantly improve the ability of $r(.)_{it}^{\text{new}}$ to fit of the cross-sectional variation of interest rates across new borrowers.

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

In the appendix we consider two alternative measures of the interest-rate gap. The first, is the average positive interest-rate gap. This measure is constructed with a version of equation (**??**) using only the mortgages for which $r_{it}^{\text{old}} > r\left(\text{FICO}, \text{region}\right)_{it}^{\text{new}}$. The second measure is the average gap between the current mortgage rate and the refinancing threshold rate computed by Agarwal, Driscoll and Laibson (2013). This threshold rate is optimal under particular assumptions.[3] As it turns out, our results are very robust to using these alternative measures.

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

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

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

[3]This threshold is computed under two assumptions. First, real mortgage interest rate and inflation are Brownian motions. Second, the mortgage is structured so that its real value remains constant until an endogenous refinancing event or an exogenous Poisson repayment event.

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

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

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

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

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

$$\text{Savings}_t = \left[\sum_{k=t}^{T} \frac{\text{Payment}^{old} - \text{Payment}^{new}}{(1+r^{new})^{(k-t)}}\right] - \frac{\text{Balance}_T}{(1+r^{new})^{T-t}}, \tag{2}$$

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

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

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

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

$$A_{2t} = \frac{1}{n_t} \sum_{i=1}^{n_t} \text{Savings}_{it}. \tag{3}$$

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

We now discuss the empirical properties of our two measures. Figure 1 displays the real 30-year mortgage rate constructed using the 30-year annualized expected inflation rate obtained from the Federal Reserve Bank of Cleveland.[4] Notice that there are several turning points in these data. For illustrative purposes, we focus on two of these points: 1997q4 and 2000q4.

Figure 2 displays the distribution of the interest-rate gap across mortgages in 1997q4 and 2000q4. The two distributions are very different. In 1997q4, about 60 percent of mortgages had a positive interest-rate gap. In contrast, only 10 percent of mortgages had a positive interest-rate gap in 2000q4. Similarly, the average interest-rate gap was much higher in 1997q4 (0.55 percent) than in 2000q4 (-1.3 percent).

Figure 3 displays the distribution of Savings_t in 1997q4 and 2000q4. Again, the two distributions are very different. In 1997q, Savings_t was positive for 60 percent of the mortgages. By 2000q4, only 10 percent of mortgages had positive savings. Similarly, average potential savings were also much higher in 1998q1 ($\$3,320$) than in 2000q4 ($-\$5,632$).

We also considered a measure of savings from refinancing constructed with a version of equation (**??**) that uses only mortgages for which $\text{Savings}_{it} > 0$. As it turns out, our results are very robust to using this alternative measure.

5 Empirical results

In this section, we study how the impact on refinancing activity of a change in the mortgage rate depends on the distribution of potential savings from refinancing. First, we establish some basic correlations estimated with ordinary least squares (OLS). Second,

[4]This expected inflation measure is constructed using Treasury yields, inflation data, inflation swaps, and survey-based measures of inflation expectations according the methodology described in Haubrich, Pennacchi, and Ritchken (2011).

we develop and 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. Third, we display how this marginal effect has varied over time. Finally, we show that an increase in refinancing translates into a broader increase in economic activity.

5.1 State dependency and the efficacy of monetary policy

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

$$\rho^c_{t+4} = \beta_0 X^c + \beta_1 \Delta R^M_t + \beta_2 \Delta R^M_t \times A^c_{j,t-1} + \beta_3 A^c_{j,t-1} + \eta^c_t. \tag{4}$$

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.[5] The variable $A^c_{j,t-1}$ is a measure of the benefits from refinancing in county c at time $t-1$. When $j=1$, $A^c_{j,t-1}$ is the average interest-rate gap for mortgages in county c. When $j=2$, $A^c_{j,t-1}$ is the average savings for mortgages in county c. The coefficient β_1 measures the effect of a change in mortgage rates when $A^c_{j,t-1}$ is zero. The coefficient β_2 measures how the effect of an interest rate change depends on the level of $A^c_{j,t-1}$. The identification of β_1 and β_2 comes from both cross-sectional and time-series variation in the response of refinancing to interest rate changes.[6]

Panels A and B of Table 1 report results for the case where $A^c_{j,t-1}$ is the average interest-rate gap and the average savings from refinancing, respectively. Column 1 reports results when regression (**??**) is estimated by OLS. In both panels, β_1 and β_2 are statistically significant at least at a 5 percent significance level. While suggestive, it is

[5] 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.

[6] 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.

hard to give a causal interpretation to these results because of potential endogeneity bias caused by any omitted variable that affects both mortgage rates and savings from refinancing. For example, suppose that during a recession more people are unemployed and therefore less willing to incur the fixed costs associated with refinancing. Also, suppose that the recession occurred because the Fed raised interest rates. Then, ΔR_t^M and $\Delta R_t^M \times A_{j,t-1}^c$ would be positively correlated with η_t^c creating a downward bias in β_1 and β_2.

To deal with the endogeneity problem, we estimate regression (**??**) using an IV strategy. We use two instruments for ΔR_t^M that exploit exogenous changes in monetary policy. The instruments are based on high-frequency movements in the Federal Funds futures rate and the two-year Treasury bond yield in a small window of time around Federal Open Market Committee (FOMC) announcements.[7]

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

$$\epsilon_t = \frac{D}{D-t}\left(y_{t+\triangle^+} - y_{t-\triangle^-}\right). \tag{5}$$

Here, t is the time when the FOMC issues an announcement, $ff_{t+\triangle^+}$ is the Federal Funds futures rate shortly after t, $ff_{t-\triangle^-}$ is the Federal Funds futures rate just before t, and D is the number of days in the month. The $D/(D-t)$ term adjusts for the fact that the Federal Funds futures settle on the average effective overnight Federal Funds rate. We consider a 60-minute window around the announcement that starts $\triangle^- = 15$ minutes before the announcement. This narrow window makes it highly likely that the only relevant shock during that time period (if any) is the monetary policy shock. Following Cochrane and Piazessi (2002) and others, we aggregate the identified shock to construct a quarterly measure of the monetary policy shock. This aggregation relies on the assumption that shocks are orthogonal to economic variables in that quarter. The standard deviation of the implied monetary policy shock is 0.12.

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

In the appendix, we redo our empirical analysis for a monetary policy shock measured using the 2-year Treasury yield:

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

Instrumental variable results. We begin by providing evidence that monetary policy shocks are a strong instrument for changes in mortgage rates. First, we show that monetary policy shocks significantly affect mortgage rates. To this end, we estimate via OLS the contemporaneous change in the 15 and 30 year mortgage rate after a one percentage point monetary policy shock. We obtain point estimates of 60 and 59 basis points with corresponding standard errors of 28 and 25 basis points for 15 and 30 year mortgages, respectively. So, both estimates are significant at a 5 percent level. Taking sampling uncertainty into account, our estimates are consistent with those of Gertler and Karadi (2015), which range from 0.17 to 0.48.

Second, we estimate the following first-stage regressions are:

$$\begin{aligned} \Delta R^M_t &= \alpha_0 + \alpha_1 \varepsilon_t + \alpha_2 \varepsilon_t \times A^c_{j,t-1} + \eta_{1t}, \\ \Delta R^M_t A^c_{j,t-1} &= \gamma_0 + \gamma_1 \varepsilon_t + \gamma_2 \varepsilon_t \times A^c_{j,t-1} + \eta_{2t}. \end{aligned}$$

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

Column 2 of Table 1 reports our benchmark IV estimates of the coefficients in regression (**??**). Other than county fixed effects, the benchmark regression does not include additional controls because they are not necessary under the null hypothesis that the monetary policy shocks are valid instruments.

Consider first the results for the case where $A^c_{j,t-1}$ is the average interest-rate gap. Both β_1 and β_2 are significant at the one percent significance level. To interpret these coefficients, suppose that all the independent variables in 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 2 of Panel A of Table 1 imply that a 25 basis points drop in mortgage rates raises the share of loans refinanced to 8.6 percent. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of -14 basis points plus one standard deviation 70 basis points. Then, a 25 basis points drop in mortgage rates raises the share of loans refinanced to 15.4 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 6.8 percent. This effect is large relative to the average annual refinancing rate, 8.5 percent.

Consider next the results for the case where $A^c_{j,t-1}$ is the average of savings from refinancing. Here, both β_1 and β_2 are significant at the one percent level. To interpret these coefficients, suppose that all the independent variables in regression (**??**) are initially equal to their time-series averages and that average of savings are initially equal to its mean value of $-\$294$. Our estimates in column 2 of Panel B of Table 1 imply that a 25 basis points drop in mortgage rates raises the share of loans refinanced to 10.7 percent. Now suppose that the drop in mortgage rates happens when the average savings from refinancing is equal to $\$2,130$, which is the mean value of $(-\$294)$ plus one standard deviation ($\$2,424$). Then the refinancing rate rises to 13.6 percent. So, the marginal impact of a one standard deviation increase in the average savings from refinancing is 2.9 percentage points.

We now consider the robustness of our results to including various controls in our analysis. To this end, we estimate the following regression using our IV procedure:

$$\rho^c_{t+4} = \beta_0 X^c + \beta_1 \Delta R^M_t + \beta_2 \Delta R^M_t \times A^c_{j,t-1} + \beta_3 A^c_{j,t-1} + \beta_4 Z_{t-1} + \eta^c_t.$$

Here, the vector Z_{t-1} denotes a set of time-varying controls. Motivated by results in Nakamura and Steinsson (2018), we first 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).[8]

Our estimates are reported in columns 3 of Table 1. Consider first the results for the case where $A^c_{j,t-1}$ is the average interest-rate gap reported in Panel A. The key finding is that including these controls has little impact on our results, certainly not on the key parameter of interest, β_2. The point estimates of β_2 are higher once we include the additional controls. But, taking sampling uncertainty into account, the estimates of β_2 are not significantly affected by the presence of the controls. Next consider the results for the case where $A^c_{j,t-1}$ is the average savings, reported in Panel B. The point estimates of β_1 and β_2 rise and are statistically significant at the one percent significance level.

Next, we use our IV procedure to estimate a version of our regression that also includes Z^c_{t-1}, a set of time-varying county controls:

$$\rho^c_{t+4} = \beta_0 X^c + \beta_1 \Delta R^M_t + \beta_2 \Delta R^M_t \times A^c_{j,t-1} + \beta_3 A^c_{j,t-1} + \beta_4 Z_{t-1} + \beta_5 Z^c_{t-1} + \eta^c_t. \quad (6)$$

The variable Z^c_{t-1} includes the following county-level controls: the unemployment rate, average log-change in real home equity, median age, share of employment in manufacturing, share of college educated and a Herfindahl index of the mortgage sector.[9] 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 report our results in column 4 of Table 1. Consider first the results for the case where $A^c_{j,t-1}$ is the average interest-rate gap, reported on Panel A. The estimated values of β_1 and β_2 are statistically significant at the one percent significance level. Taking sampling uncertainty into account, the values of these coefficients are similar our benchmark estimates.

[8]The data was obtained from the Federal Reserve Bank of Philadelphia, https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files

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

Consider next the results, reported in Panel B, for the case where $A^c_{j,t-1}$ is the average of savings from refinancing. For both policy shock measures the estimates of β_1 and β_2 are statistically significant at least at the five-percent significance level. The values of β_1 and β_2 are somewhat higher than the benchmark estimates.

Finally, as a further robustness test, we also included in regression (**??**) interactions of the form $\Delta R^m_t Z^c_{t-1}$. We describe these effects in the Appendix. The implied estimates of β_2 are statistically indistinguishable from those reported in columns 4 of Table 1. The fact that including the interaction terms does not change the estimated elasticities implies that the state dependency that we highlight is distinct from other potential mechanisms explored in the literature. These mechanisms include, for instance, differential responses in refinancing to a decline in mortgage rates due to differences in competitiveness of the local lending market. It is also distinct from state dependency related to variation in the value of home equity across counties.

5.2 Refinancing and economic activity

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

We begin by considering the regression where the dependent variable is the annual log-change in new building permits:

$$\Delta \log \text{ Permits}_{t,t+4} = \theta_0 X^c + \theta_1 \Delta R^M_t + \theta_2 \Delta R^M_t \times A^c_{j,t-1} + \theta_3 A^c_{j,t-1} + \eta^c_t, \qquad (7)$$

Our results are reported in Table 3. Panel A and B report results for the case where $A^c_{j,t-1}$ is the average interest-rate gap and average savings from refinancing, respectively. Column 1 reports results when regression (**??**) is estimated by OLS. In both panels, θ_1

and θ_2 are statistically significant at least at a 5 percent significance level. Column 2 of Table 3 reports the IV estimates of regression (**??**).

Consider first the results for the case where $A^c_{j,t-1}$ is the average interest-rate gap. Both θ_1 and θ_2 are significant at least at a one percent significance level. To interpret the point estimates suppose that all the independent variables in regression (**??**) are initially equal to their time-series averages. The estimates in column 2 imply that a 25 basis points drop in mortgage rates raises the percentage change in new permits to 17.0. Now suppose that the drop in mortgage rates happens when the average interest-rate gap is equal to 56 basis points, which is the mean value of (-14 basis points) plus one standard deviation (70 basis points). Then a 25 basis points drop in mortgage rates raises the percentage change in new permits to 23.6 percent. So, the marginal impact of a one standard deviation increase in the average interest-rate gap is 6.6. This effect is large relative to a one standard deviation change in housing permits, which is 26 percent.

Consider next the results for the case where $A^c_{j,t-1}$ is the average of savings from refinancing. Both θ_1 and θ_2 are significant at the one percent level. Our estimates in column 2 of Table 3, Panel B imply that a 25 basis points drop in mortgage rates raises the percentage change in new permits to 14.1 percent. Now suppose that the drop in mortgage rates happens when the average savings from refinancing is initially equal to $\$2,130$, which is the mean value of ($-\$294$) plus one standard deviation ($\$2,424$). Then, the refinancing rate rises to 22.6 percent. So, the marginal impact of a one standard deviation increase in the average savings from refinancing is 8.5 percentage points. Finally, as a further robustness test, we include time-varying county-level controls in regression (**??**). The implied estimates of θ_2 reported in column 4 are not statistically different from those reported in column 2.

Overall, we view the results of this section as providing strong support for two hypotheses. First, the effect of a change in the interest rate on refinancing activity is state dependent. When measures of the average gains from refinancing are high, a given

fall in interest rate induces a larger rise in refinancing activity. Second, the effect of a change in the interest rate on economic activity, as measured by new housing permits, is state dependent in a similar way. This result 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 state-dependant rise in auto registrations when interest rates fall. Taken together, these results imply that the effect of a change in monetary policy is state dependent.

6 A life-cycle model

To analyze the state dependency of monetary policy, we develop a version of the life-cycle model of mortgage refinancing proposed in Wong (2016) that allows for state dependency in the aggregate state variables. We use the model for two purposes. First, to interpret our empirical results on the state dependency of the refinancing channel of monetary policy. Second, to study the impact of the observed long-term decline in refinancing costs on the efficacy and state dependency of monetary policy.

It is evident that there is a great deal of heterogeneity across households in their propensity to refinance in response to an interest rate cut. One way to capture that heterogeneity in refinancing behavior is to allow for a great deal of heterogeneity in unobserved fixed costs of refinancing. An alternative, is to model that heterogeneity in refinancing behavior as reflecting demographics, initial asset holdings and idiosyncratic income shocks. We choose the second strategy to minimize the role of unobservable heterogeneity.

The economy is populated by a continuum of people indexed by j. We think of the first period of life as corresponding to 25 years of age. Each person can live up to 60 years. The probability of dying at age a is given by $1 - \pi_a$. Conditional on surviving,

people work for 40 years and retire for 20 years. People die with probability one at age $T = 85$.

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

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

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

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

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

$$\log(y_{jat}) = \chi_a + \eta_{jt} + \phi_a Y_t. \tag{8}$$

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

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

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

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

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

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:

$$M_{ja\tau} = \frac{b_{ja\tau}}{\sum_{k=1}^{m(a)}(1 + R_{ja\tau})^{-k}}. \tag{9}$$

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

$$R_{jat} = r_t.$$

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

Loan-to-value constraint. The size of a mortgage loan must satisfy the constraint:

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

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

State variables. The state variables are given by $z = \{a, \eta, K, S\}$. Here, a, η, and K denote age, idiosyncratic labor income, and asset holdings, respectively. The vector

K includes short-term asset holdings (s), the housing stock (h^{own} for homeowners, zero for renters), the mortgage balance (b for homeowners, zero for renters), and the interest rate (R) on an existing mortgage. Finally, S denotes the aggregate state of the economy which consists of the logarithm of real output, y_t, the logarithm of real housing prices, p, the real interest rate on short-term assets, r, and the logarithm of economy-wide average positive savings from refinancing, A. We assume that S_t is a stationary stochastic process.

Mortgage interest rate and rental rates. It is well known that 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 directly specify with reference to the data. This approach allows the model to be consistent with the empirical properties of these variables.

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

$$r_t^m = a_0^m + a_1^m r_t + a_2^m y_t. \tag{10}$$

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

The rental rate is given by:

$$\log(p_t^r) = \alpha_0 + \alpha_1 r_t + \alpha_2 y_t + \alpha_3 p_t. \tag{11}$$

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

$$V(z) = \max\left\{V(z)^{\text{rent}}, V(z)^{\text{own \& no-adjust}}, V(z)^{\text{own \& adjust}}\right\} \tag{12}$$

A renter maximizes

$$V(z)^{\text{rent}} = \max_{c,h^{\text{rent}},s'} u\left(c, h^{\text{rent}}\right) + \beta E\left[V(z')\right] \tag{13}$$

subject to the budget constraint,

$$c + s' + p^r h^{\text{rent}} = y + (1-\delta)ph^{\text{own}} + (1+r)s - b(1+R), \tag{14}$$

and the borrowing constraint on short-term assets,

$$s' \geq 0.$$

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

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

A homeowner who does not refinance his mortgage maximizes:

$$V(z)^{\text{own \& no-adjust}} = \max_{c,s'} u\left(c, h^{\text{own}}(1-\delta)\right) + \beta E\left[V(z')\right] \tag{15}$$

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 (**??**).

A homeowner who refinances, maximizes:

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

subject to the budget constraint

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

the borrowing constraint on short term assets,

$$s' \geq 0,$$

the minimal down payment required on the mortgage,

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

The new mortgage interest rate is given by:

$$R' = r^m.$$

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

6.1 Calibration

Our parameter values are summarized in Table 4. We adopt the same values as Wong (2018) for the parameters associated with preferences (σ, B, β, and α), idiosyncratic income (ρ_η, σ_η, χ_a, and ϕ_a), house depreciation (δ), the loan-to-value constraint (ϕ), the process for mortgage rates (a_0^m,a_1^m, and a_2^m in equation (**??**)) and the process for rental rates (α_0, α_1, α_2, and α_3 in equation (**??**)). See Wong (2018) for a description of the calibration procedure underlying these parameter choices. In addition, we choose the fixed cost, F, to equal approximately $\$2,100$ (2 percent of median house price) to

match the average quarterly fraction of new loans of 4.5 percent.[11] Recall that we think of the first period of life as 25 years of age. Age-dependent survival probabilities are given by the U.S. actuarial life-expectancy tables and assume a maximum age of 85. Assets and income in the first period are calibrated to match average assets and income for persons of ages 20 to 29 in the 2004 Survey of Consumer Finances.

6.2 The evolution of the aggregate states

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

Recall that we model the mortgage rate with maturity m as a function of r_t and y_t (see equation (**??**)). We estimate this function using OLS. Table 5 reports our results. Figure 4 shows that the estimated version of equation (**??**) does a very good job at accounting for the time-series behavior of the 15- and 30-year mortgage rates over the period 1990-2007.

We also model the rental rate as a linear function of r_t, y_t and p_t (see equation (**??**)). We estimate this function using the national house price and rent indices obtained from the Federal Reserve Bank Dallas.[12]

Figure 5 shows that the estimated version of equation (**??**) 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 $1989 - 2007$.

We estimated a suite of quarterly time-series models for the aggregate state vector S_t. Recall that S_t consists of r_t, y_t, p_t, and a_t (the logarithm of economy-wide

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

[12] These data are available at https://www.dallasfed.org/institute/houseprice.

average positive savings from refinancing). We eliminated from consideration models with explosive dynamics. We judged the remaining models balancing parsimony and the implied average (over time and across variables) root-mean-square-error (RMSE) of one-year-ahead forecasts. Parsimony is important for the computational tractability of our structural model.

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

$$\Delta S_t = B_1 \Delta S_{t-1} + B_2 \Delta r_{t-1} a_{t-1} + u_t. \tag{16}$$

Here, B_1 is a 4×4 matrix, B_2 is a 4×1 vectors, and u_t is a Gaussian disturbance.

The appendix reports the average RMSE for the alternative models that we considered. These models include specifications with up to four lags of ΔS_t and $\Delta r_{t-1} a_{t-1}$. In addition, we included cross products of all the variables in different combinations as well as squares and cubes of the different variables. We also considered different moments of different measures of the gains from refinancing. For example, we replace a_t with average savings (in levels), median savings, average interest-rate gap, logarithm of average positive interest-rate gap, median of the interest-rate gap, fraction of mortgages with positive savings, and standard deviation of savings.

None of the RMSE associated with the alternative specifications was smaller, taking sampling uncertainty into account than the RMSE associated with specification (**??**). At the same time, specification (**??**) 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 (**??**). This table also reports the average RMSE computed over time and over the four variables included in S_t. The coefficients in B_2 are statistically significant at the one percent level for r_t and p_t and at the 10 percent level for $\log(S_t)$.

A natural question is whether the inclusion of a_t and $\Delta r_{t-1} a_{t-1}$ in specification (**??**) helps reduce the RMSE for the three aggregate variables (r_t, y_t, p_t) that people need to forecast to solve their problem. Simply adding a_t to a linear VAR for r_t, y_t, p_t,

reduces the average RMSE for r_t, y_t, 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 r_t, y_t, p_t.

6.3 Some empirical properties 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 agents have the distribution of assets, liabilities and mortgage rates observed in the data. We feed the realized values of r_t, y_t, and p_t for the period from 1995 to 2007. We simulate the idiosyncratic component of income, y_{jat}, for each household in our model.

Life-cycle dynamics. Consider first the model's ability to account for the behavior of U.S. households as a function of age. Figure 6 displays home ownership rates, as well as the logarithm of non-durable consumption, debt ratios and household net wealth. The model does a reasonably good job of accounting for these moments of the data. The model implies that home ownership rates rise with age and stabilize when agents reach their 40s.

To understand the mechanisms that underlie Figure 6, it is useful to do a simplified analysis of the cost of owning versus renting.[13] The net benefit of owning a home is given by:

$$\frac{p_t^r}{p_t} + E_t \frac{p_{t+1} - p_t}{p_t} - r_t \left(1 - \frac{b_t}{p_t}\right) - \frac{b_t}{p_t} r_t^m - \delta - r_t \frac{F}{p_t}. \tag{17}$$

The first term in equation (**??**) is the savings from not paying rent, which we express as a fraction of the house price, p_t^r/p_t. In our sample, p_t^r/p_t is on average 7.7 percent. The second term in this expression is the expected real rate of housing appreciation.

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

In our calibration, $E_t\left(p_{t+1}-p_t\right)/p_t$ is on average one percent per year. The third term is the opportunity cost of the down payment, $1-b_t/p_t$ on a house. The fourth term is the mortgage payment on the house, where r_t^m denotes the average mortgage rate. We estimate that the average value of r_t and r_t^m in our sample is 3.5 percent and 6.5 percent, respectively. The fifth term, δ, is the rate of depreciation of the housing depreciation of the housing stock. We assume that δ is three percent per annum. The last term in equation (**??**) is the fixed cost of buying a house as a percentage of the house price. Recall that we assume $F = \$2,100$ which represents roughly one percent of the average price of a house in our sample ($\$189,000$).

A number of observations follow from equation (**??**). First, other things equal, the higher are the rental-price ratio and the expected real rate of housing appreciation, the more attractive it is to own rather than rent a house. Second, other things equal, the less expensive is the house (i.e. the lower is p_t) the larger is the negative impact of a fixed cost on the desirability of purchasing a home ($r_t F/p_t$). Third, other things equal, the lower the down payment, 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:

$$r_t+\frac{b_t}{p_t}\left(r_t^m-r_t\right). \tag{18}$$

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 $\left(r_t^m-r_t\right)$. 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 6. The model implies that home ownership rates rise as people get older. This result follows the fact that, on average, income rises as a person ages, peaking between 45 and 55 years of age. As income rises, people want to live in bigger homes, which reduces the impact of fixed

costs on the desirability of purchasing a home ($r_t F/p_t$). Also, as income rises, people can afford bigger down payments on those homes, which, as we just discussed, reduces the user cost of owning a home. Taken together, both forces imply that home ownership should on average rise until people are 55. Thereafter, home ownership rates roughly stabilize. However, many elderly homeowners downsize. They do this by selling their old homes and using the proceeds to buy a smaller home with relatively small mortgages. They use these homes as vehicles to fund their bequests.

From Figure 6 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 6 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.

Refinancing and the interest-rate gap. In the data the average annual refinancing rate is 8.5 percent with a standard deviation of 4 percent. In the model the average annual refinancing rate is 7.5. So, taking sampling uncertainty into account, the model does a good job at accounting for the average refinancing rate. The model is also consistent with the fraction of new mortgages issued in each period. This fraction is 25 percent both in the model and the data.

Figure 7 plots the fraction of loans that are refinanced as a function of the interest-rate gap faced by people in the economy. We display these statistics both for the data and the model. The data-based statistics are computed as follows. We bin all the loans according to the interest-rate gap ranges indicated in the figure. For every bin, we calculate the fraction of loans that were refinanced. Figure 7 displays these fractions and the corresponding 95 percent confidence intervals.

The model-based statistics are computed as follows. The initial distribution of age, assets, mortgage debt and mortgage rates is the same as the actual distribution in 1994. People who die in the model at time t are replaced by 25-year olds. The distribution of assets, mortgage debt, and mortgage rates across these new people is the same as that observed in the data at time t. We assume there are 100,000 households in the model economy and draw idiosyncratic shocks for each of these people. At each point in time, we feed in the actual values of the aggregate state of the economy from 1995 to 2007 for r_t, y_t, and p_t. We use the model to construct the time series on A_t, the logarithm of economy-wide average positive savings from refinancing. People use this variable to form expectations for future aggregate states using equation (**??**). 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 7, taking sampling uncertainty into account the model does well at accounting for the data.

Figure 8 is the analogue of Figure 7 computed using average savings rather than the interest-rate gap. With one exception, the model can account for the average fraction of mortgages refinanced as a function of average savings. The exception is that in the data there are some people who have potentially large savings from refinancing but do not act upon these. Our model understates the fraction of mortgages refinanced for the upper tail of the average savings distribution.[14]

[14]See Stanton (1995), Deng, Quigley, and Van Order (2000), and Andersen, Campbell, Nielsen, and Ramadorai (2015) for evidence that some agents do not refinance their fixed-rate mortgage when

7 State dependent effects of monetary policy

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

$$\rho_{t+4} = \beta_0 + \beta_1 \Delta R_t^M + \beta_2 \Delta R_t^M \times A_{j,t-1} + \beta_3 A_{j,t-1} + \eta_t, \tag{19}$$

Regression (**??**) is a version of regression (**??**) without county fixed effects. We estimate regression (**??**) using the monetary policy shock as instruments. Table 7 reports the model-based and data-based estimates of β_1 and β_2. The data estimates are reproduced from column 2 of Panel A and B, Table 7. Consider first the results when the benefits of refinancing are measured with the interest-rate gap. From Table 7 we see that the model does quite well at accounting for the regression results. Taking sampling uncertainty into account, the model- and data-based estimates are not significantly different from each.

Consider next the results when the benefits of refinancing are measured with average savings. The model succeeds in accounting for the signs of both β_1 and β_2. However, the model understates the magnitude of our data-based estimate of β_2.

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

$$c_{jt+1} - c_{jt} = \beta_{j0}^c + \beta_1^c \Delta R_t^M + \beta_2^c \Delta R_t^M \times A_{j,t-1} + \beta_3^c A_{j,t-1} + \eta_t^c. \tag{20}$$

The coefficients in this regression are estimated using the monetary shocks as instruments. Column 1 of Table 8 shows the effect of a 25 basis points fall in interest rates starting from steady state. The total effect on consumption of an exogenous change in mortgage rates is 1.03 percent. The direct effect ($\beta_1^c \Delta R_t^M$) is 0.6 percent. The state-dependent effect ($\beta_2^c \Delta R_t \times$ average interest-rate gap) is 0.42 percent.

market rates fall below their locked-in contact rate. Stanton (1995) and Deng et al (2000) explain this phenomenon by assuming heterogeneity in refinancing costs. Anderson et al (2015) stress the role of heterogeneity in inattention.

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

Roughly 80 percent of the households that refinance engage in cash-out refinancing, that is, the size of their new mortgage is larger than the balance of the old mortgage. This value is in line with the evidence presented by Chen, Michaux, and Roussanov (2013). Using a conservative estimate based on conforming mortgages, these authors argue that over the period 1993-2010 on average about 70 percent of refinanced loans involve cash-out.

In our model, we abstract from the effects of refinancing decisions on bank owners. If those owners are constrained and the profits of the bank rise or fall one to one by the amount that consumers save by refinancing, the refinancing channel has no aggregate effect on consumption. However, it is natural to assume that bank owners behave like unconstrained households. Under this assumption, the negative effect of refinancing on the consumption of bank owners is much smaller in absolute value than the positive effect on the consumption of constrained households.[15] As a result, the overall effect of

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

refinancing on aggregate consumption is positive.

7.1 Model experiments

In this subsection, we use our model to illustrate the state-dependent nature of the effects of monetary policy. We begin by comparing the power of a given interest rate cut in two scenarios. In both scenarios, the economy starts in the steady state, by which we mean that the aggregate state variables have been constant and equal to their unconditional means. However, agents have been experiencing ongoing idiosyncratic shocks to their income.

In the first scenario, we consider the effect of an interest rate cut when the economy starts in the steady state and remains in the steady state for five periods. We then feed in an interest-rate shock such that the interest rate falls by 100 basis points in time period six. This path is displayed in Figure 9. At each point in time, agents form expectations according to equation (**??**). Table 8 reports the impact of the interest rate cut at time six on refinancing and consumption. Notice that 24.5 percent of people refinance in the impact period of the shock and there is a 2.4 percent increase in aggregate consumption. There are two reasons why the effects are so large. First, everybody has a positive rate gap after the interest rate cut. This property reflects the fact that all mortgage rates prior to time six had an interest rate equal to the steady-state interest rate which is higher than the new interest rate. Second, people expect the interest rate to revert to the mean so period six is a good time to refinance.

We now turn to the second scenario in which the central bank steadily raises interest rates starting in period one until they peak in time period five. The central bank then cuts interest rates by 100 basis points in period six. This path is displayed in Figure 9. Table 8 indicates that only 3.2 percent of agents refinance in the impact period of the shock and there is only a 0.3 percent rise in consumption. The reason for these small effects relative to the first scenario is that only 26 percent of people face a positive interest-rate gap in period 6. These are the people who entered new mortgages despite

rising interest rates due to life-cycle considerations or idiosyncratic shocks to income prior to time six. Recall that in steady state, there are 25 percent new mortgages every year.

These results imply that past actions of the Fed can have effects on the future impact of monetary policy on refinancing. The reason is that past Fed actions change the distribution of future potential savings across borrowers.

7.2 Effects of a fall in the cost of refinancing

We also use our model to study the implications of a decline in the cost of refinancing. Various authors argue that such a decline is occurring because of the emergence of Fintech lenders. The market share of Fintech lenders in mortgage markets has increased from 4 to 15 percent between 2007 and 2015 (Buchak et. al. (2017)). This growth has been particularly pronounced for refinances.

Using loan-level data on U.S. mortgage applications and originations, Fuster et. al. (2018) show that Fintech lenders process mortgage applications about 20 percent faster than other lenders, after controlling for detailed loan, borrower, and geographic observables. They also find that in areas with more Fintech lending, borrowers refinance more. This evidence is consistent with the idea that Fintech is reducing the fixed costs of refinancing. This reduction is consistent with other evidence that competition lowers direct costs from refinancing such as origination fees. Ambrose and Conklin (2013) show that the average number of brokers per MSA increased steadily to a peak of 65 in mid-2004, while average origination fees declined from over 5 percent at the beginning of 1998 to less than 2.5 percent at the end of 2004.

While it is hard to forecast how much the fixed costs of refinancing will decline due to the evolution of Fintech, it seems clear that they will decline substantially. A natural question is: what is the effect of a decline in the cost of refinancing on the magnitude and state-dependent nature of the refinancing channel of monetary policy.

Table 9 compares the effect of a 25 basis points interest rate cut on refinancing

activity and consumption for two values of the fixed cost: $\$2,100$ (our benchmark calibration value) and $\$1,000$. We simulate both versions of the model following the procedure described in Section 5.3. Using simulated data, we estimate β_1 and β_2 in regression (**??**) using the monetary shocks as instruments. We use the same data to estimate the following regression where the dependent variable is the annual change in the logarithm of consumption (c_t):

$$c_t - c_{t-1} = \beta_0^c + \beta_1^c \Delta R_t^M + \beta_2^c \Delta R_t^M \times A_{j,t-1} + \beta_3^c A_{j,t-1} + \eta_t^c.$$

Table 9 shows the effect of a 25 basis points fall in interest rates starting from steady state for two values of the refinancing cost: $\$2,100$ (the value used in our calibration) and $\$1,000$. We see that reducing fixed costs from $\$2,100$ to $\$1,000$ leads to a large fall in the state-dependent nature of the effects of monetary policy. For refinancing, this effect ($\beta_2 \Delta R_t \times$ average interest-rate gap) falls from 1.81 to 1.12 percent. For consumption ($\beta_2^c \Delta R_t \times$ average interest-rate gap), this effect falls from 0.42 to 0.36 percent.

At the same time, the fall in fixed costs increases the direct effect of the interest rate cut. For refinancing, this effect ($\beta_1 \Delta R_t$) rises from 0.95 to 2.9 percent. For consumption, this effect ($\beta_1 \Delta R_t$) rises from 0.60 to 0.88 percent.

In sum, our model implies that, as transactions costs of refinancing fall, the effects of monetary policy become larger but less state dependent. The intuition for the state-dependency result is straightforward. When transactions costs are lower, consumers refinance more often. As a result, interest rates on existing mortgages are more closely distributed around current mortgage rates.

The intuition for why monetary policy is more powerful when transactions costs are low is also straightforward. More people refinance in response to an interest rate cut. Many people are against their borrowing constraint. These people engage in cash-out refinancing to increase their consumption.

8 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. The model allows us to study the effects on monetary policy of a decline in refinancing costs. Based on this experiment we argue that the expansion of Fintech will make monetary policy less state dependent but more powerful.

We focus on the effects of monetary policy in systems where mortgages are primarily fixed rate. Examples of countries with such systems include the U.S., Canada, Switzerland, and the Netherlands.[16] However, there are many countries where mortgages are primarily variable rate. Examples include Australia, Ireland, Korea, Spain, and the U.K.

The state dependent effects of monetary policy that arise because of the refinancing channel in a fixed rate system do not arise in a variable mortgage rate system. The reason is that there are no unexploited refinancing opportunities in a variable rate system. So, even if Fintech succeeds in driving refinancing costs to very low levels, the monetary transmission mechanism of the U.S. will not converge to that of countries with variable interest rate mortgages.

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[16]There are significant differences in the maturity of fixed rate mortages in these countries. See Lee (2010) for a discussion.

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A simple way to see this property in our model is to compute the steady-state distribution of interest-rate gaps for the two levels of fixed costs. These distributions are displayed in Figure 10. In addition to featuring low dispersion, the interest-rate gap distribution is more stable over time when transactions costs are low.

Tables and Figures

Table 1: State dependency of monetary policy and refinancing

Refinancing over the year	**OLS**	**IV**		
	(I)	**(II)**	**(III)**	**(IV)**
Panel A				
ΔR(t)	0.075***	0.062***	0.070*	0.083***
	(0.004)	(0.021)	(0.029)	(0.026)
ΔR(t) x Average rate gap	0.039**	0.389***	0.479***	0.472***
	(0.014)	(0.075)	(0.109)	(0.102)
Panel B				
ΔR(t)	0.074***	0.103***	0.130***	0.142***
	(0.003)	(0.013)	(0.013)	(0.013)
ΔR(t) x Average savings	0.013***	0.048***	0.059***	0.056***
	(0.002)	(0.009)	(0.008)	(0.009)
County Fixed Effects	Yes	Yes	Yes	Yes
SPF Controls	No	No	Yes	Yes
Additional county controls	No	No	No	Yes

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

Table 2: First-state estimates

First stage y-variable:	**ΔR(t)**	**ΔR(t) x Average savings**
	(II)	**(II)**
Panel A:		
Ɛ(t)	1.466***	0.385***
	(0.103)	(0.033)
Ɛ(t) x Average rate gap	0.048	0.487***
	(0.256)	(0.095)
R-squared	0.734	0.557
Panel B:		
Ɛ(t)	1.583***	1.738***
	(0.113)	(0.130)
Ɛ(t) x Average savings	-0.059	0.791***
	(0.049)	(0.159)
R-squared	0.293	0.156

Notes: Regression (3), first stage estimates based on futures shock. Standard errors are in parentheses. *, **, and *** give the significance at the 10, 5, and 1 percent levels.

Table 3: State dependency of monetary policy and housing permits

Average savings	**OLS**	**IV**		
	(I)	**(II)**	**(III)**	**(IV)**
Panel A:				
ΔR(t)	0.175***	0.396***	0.356***	0.083**
	(0.019)	(0.034)	(0.036)	(0.026)
ΔR(t) x Average rate gap	0.083**	0.373***	0.111*	0.472**
	(0.021)	(0.103)	(0.076)	(0.102)
Panel B:				
ΔR(t)	0.209***	0.264***	0.290***	0.220**
	(0.019)	(0.044)	(0.049)	(0.070)
ΔR(t) x Average savings	0.012**	0.140***	0.063**	0.080**
	(0.006)	(0.027)	(0.026)	(0.036)
County Fixed Effects	Yes	Yes	Yes	Yes
SPF Controls	No	No	Yes	Yes
Additional county controls	No	No	No	Yes

Notes: Regression (6), 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 4: Model parameter values

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

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

Table 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-1}	-3.475***	0.843***
	(0.168)	(0.119)
log r_{t-1}	0.334***	-0.002***
	(0.058)	(0.001)
log p_{t-1}		-0.022
		(0.014)
constant	-0.030	3.187***
	(15.82)	(0.488)

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

Table 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)	(0.147)
log r_{t-1}	0.000	0.612***	0.010***	0.223
	(0.108)	(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
Panel A:		
ΔR(t)	0.062***	0.038
	(0.021)	
ΔR(t) x Average rate gap	0.389***	0.299
	(0.075)	
Panel B:		
ΔR(t)	0.103***	0.139
	(0.013)	
ΔR(t) x Average savings	0.048***	0.017
	(0.009)	

Notes: Regression (3), 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 8: Alternative paths of monetary policy: Model

	Rate path prior to a 1 ppt cut	Effect on refinancing	Average rate gap before cut	Change in consumption
(i)	Flat at about 3.5%	24.5%	0.0%	2.4%
(ii)	Rising from 3.5% to 8% over 5 periods	3.2%	-1.1%	0.3%

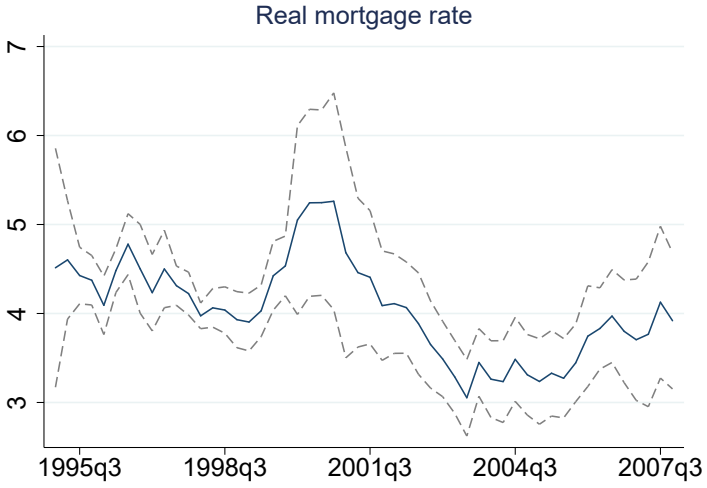
Notes: Alternative paths of monetary policy. See text for more detail.

Table 9: State dependency of monetary policy and alternative transaction costs

	Fixed cost	
	$2.1K	$1K
Effect on refinancing:		
Overall effect of a 25 bp fall in rates	2.76%	4.02%
$\beta_1 \Delta R_t$	0.95%	2.90%
$\beta_2 \Delta R_t$ times mean(φ_t)	1.81%	1.12%
Effect on consumption:		
Overall effect of a 25 bp fall in rates	1.03%	1.30%
$\beta_1 \Delta R_t$	0.60%	0.88%
$\beta_2 \Delta R_t$ times mean(φ_t)	0.42%	0.36%

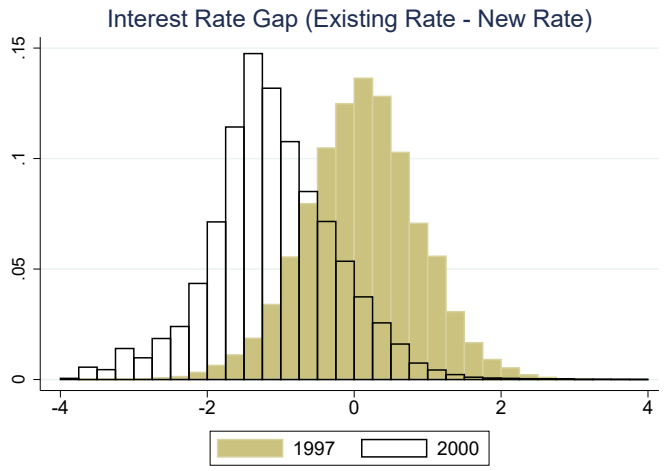
Notes: Regression (3), first stage estimates based on futures shock.

Figure 1: Real 30-year mortgage rate



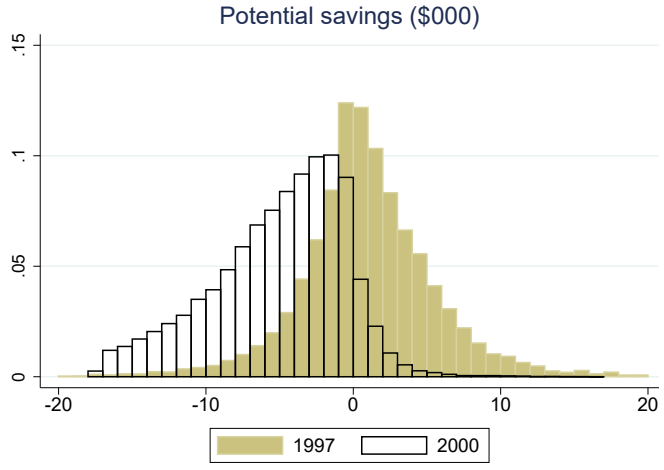
Notes: The figure depicts the average real mortgage rate from Core Logic. Dashed lines depict 1 standard deviation.

Figure 2: Distribution of interest rate gaps in 1997 and 2000



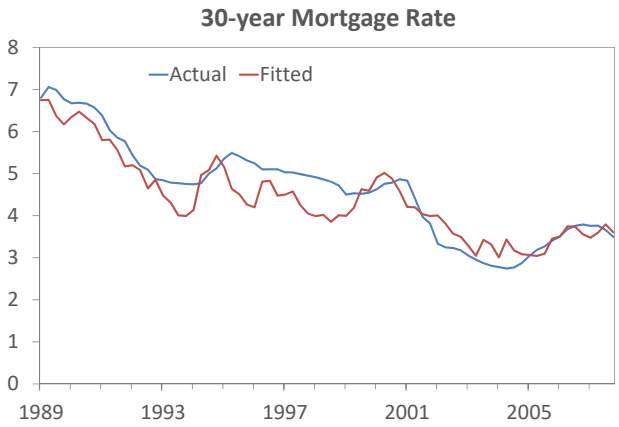
Notes: The figure depicts the distribution of interest rate gaps across borrowers. The interest rate gap is defined as the difference between the existing mortgage rate and the current market rate. See text for more details.

Figure 3: Distribution of potential savings in 1997 and 2000



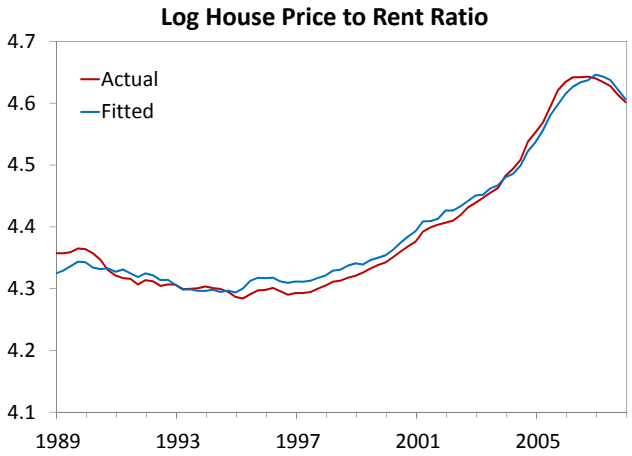
Notes: The figure depicts the distribution of potential savings across borrowers under one particular refinancing strategy, where the household refinances into a 30-year mortgage and repays the loan over the same number of periods. See text for more details.

Figure 4: Time series of fitted and actual mortgage rates



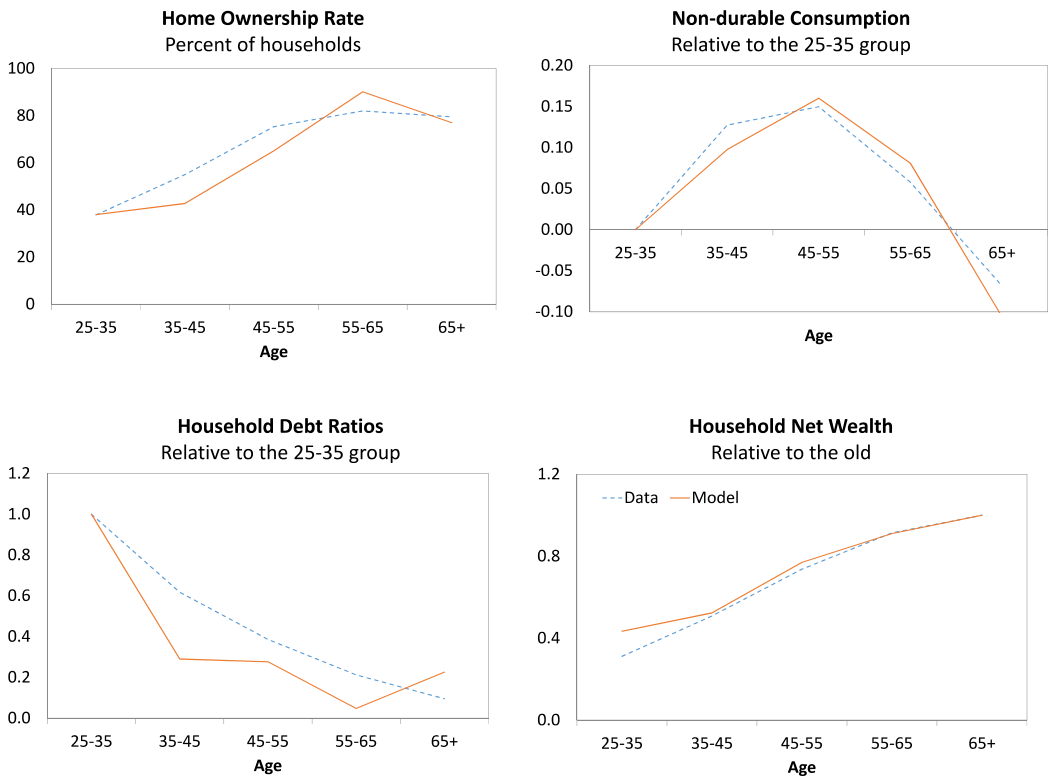
Notes: The figure depicts the fitted and actual mortgage rate data. See text for more details.

Figure 5: Time series of fitted and actual house price to rent ratios



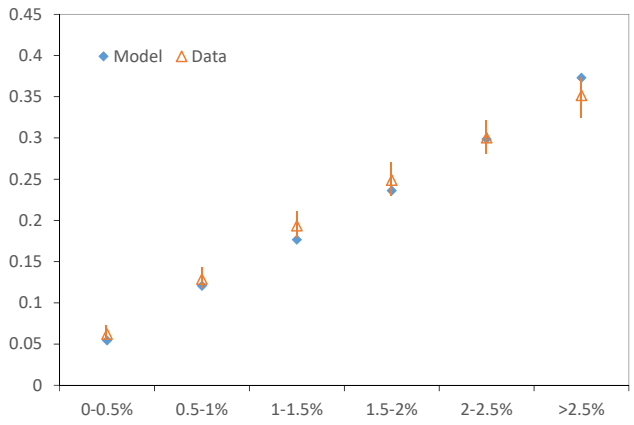
Notes: The figure depicts the fitted and actual house price to rental ratios. See text for more details.

Figure 6: Life-cycle moments



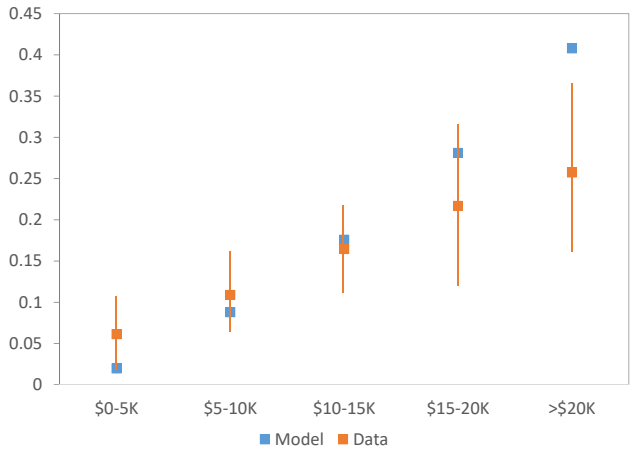
Notes: The figure depicts the fitted and actual life-cycle moments. See text for more details.

Figure 7: Refinancing, given the interest rate gap



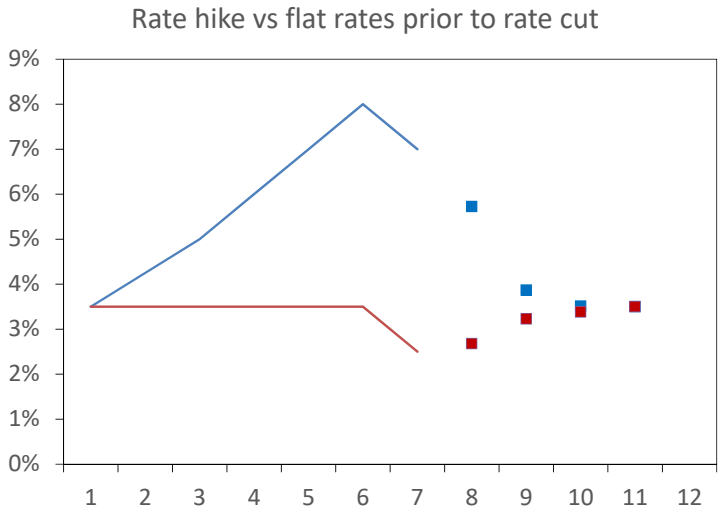
Notes: The figure depicts propensity to refinance for each given interest rate gap in the data and the model. See text for more details.

Figure 8: Refinancing, given the average potential savings



Notes: The figure depicts propensity to refinance for each given range of average potential savings in the data and the model. See text for more details.

Figure 9: Alternative interest rate paths



Notes: The figure depicts two alternative interest rate paths, starting at steady state. The dots represents expectations at time 7. See text for more details.