# Appendix For Online Publication

## A Data

### A.1 CEX Data

I obtain the micro data on the U.S. Consumer Expenditure survey (CEX) from the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan, and from the Bureau of Labor Statistics (BLS). The survey is conducted on a quarterly basis by the BLS for the main purpose of constructing the consumer price index weights. The unit of survey is the household level, and each household is interviewed by the BLS once per quarter, for at most five consecutive quarters. While expenditure is reported at the household level, demographics are reported for individuals. These include age, income, education attainment, family size, and year of birth of the head of household.

Data is collected on expenditures at a detailed level for non-durable and durable goods, and services. Similar to Krueger and Perri (2006), I define non-durable expenditure to include food, alcohol and tobacco, gasoline and other fuel, and clothing. Services expenditure covers household utilities, household operations, service charges, recreational services, public transportation, personal care services, health care, and education, and excludes housing. Durable goods expenditure includes spending on vehicles, housing furnishings, and recreational equipment. Each category of expenditure is deflated using the BLS consumer price indices.

Following Aguiar and Hurst (2013), Coibion, Gorodnichenko and Hong (2015), and others, I restrict the sample to ensure that the data is comparable over time. Specifically, I restrict the sample to include only households where the head of household is aged between 25 and 75 years (inclusive). To reliably estimate cohort effects, I include only households who are born between 1914 and 1973 inclusive, to ensure that each cohort has at least 10 years of data. The sample includes only households who report expenditures in all four quarters of the survey, and with non-zero food expenditure. Only urban households are included in the sample, since the BLS did not interview rural households prior to 1983. I also restrict households with complete income reports, and with at least three monthly observations per quarter. This leaves 235,933 households in total over the period 1980-2007.

There are some well documented measurement errors within the CEX data.[78] Over time, total spending measured by the CEX has fallen relative to the National Income and Product Accounts (NIPA) measure. Moreover, the discrepancy has differed by consumption category. I approach this measurement issue in three ways. First, I note that this discrepancy will not affect the interpretations of the age-specific estimated results in this paper if the discrepancy in reporting is uniform across the age groups. That is, the comparison of old and young households will not be affected, even though the levels of expenditure are mismeasured. Second, for robustness, I recompute age-specific elasticities for consumption categories where has been little deterioration in the ratio of the CEX spending to NIPA spending over the past two decades.[79] Third, I repeat the analysis using a separate data set, the Nielsen Homescan data (described below), which is not subject to the same

[78]For a discussion of these issues, see for example, Aguiar and Hurst (2013) and Aguiar and Bils (2011).

[79]These categories include food at home, food away from home, rent and utility, and cable and satellite television and radio services.

types of measurement issues as the CEX. The results in this paper are qualitatively robust within both the narrower CEX consumption categories and the Nielsen Homescan data.

### A.2 Nielsen data

Participating households record the data using hand-held scanners at home. The households record the store where the product was purchased, the date and quantity purchased at the Universal Product Code (UPC) level. Prices come from one of two sources. If the store where the product was purchased is one that reports prices to Nielsen as part of their store-level survey, then Nielsen obtains the price from the store data. Nielsen also reports the price paid which can include panelist-reported prices or Nielsen-ascribed prices if the panelist does not, or is not required to, enter a price.[80]

### A.3 Mortgage data

I use the CEX detailed expenditure files on owned living quarters and other owned real estate and mortgages, over the sample period is 1993-2007. Some of the variables are unavailable prior to 1993, and therefore I focus on the period starting from 1993. I obtain the data from the BLS for the period 1996-2007, and the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan for the period 1993-1995. I focus on loans related to owner-occupied, by restricting the sample to loans for purchase of properties that the home of residence. This is based on the observations with a property code equal to 100, which denotes "The home in which you (your CU) currently live(s)").

To identify a loan adjustment (new loan for purchase or on an existing property) in the sample, I first obtain the starting year and month of the transaction. Using the mortgage starting date is known, I construct a loan-adjustment binary variable that equals one if the starting date equals the current observation date. It is equal to zero otherwise, signalling an existing loan. I do not include in the sample any observations with original balances in the bottom 1% of the sample, to abstract from possible home equity lines of credit.

The "loan adjustment" variable that I define includes new loan transactions for new housing purchases, as well as refinancing of loans on existing homes. I do not separate out the two transactions, since the CEX data does not provide a link between the mortgage and the address of the home to distinguish between new purchases and refinancing. Therefore, I focus the analysis on the overall loan adjustment propensities.

The second data source that I use to examine loan-adjustment propensities is the Freddie Mac Single Family Loan-Level data.[81] This is loan-level panel data of all 30-year mortgages securitized by Freddie Mac. I merge the loan origination data file (with loan characteristic information, such as the original leverage ratios and credit scores) with the monthly panel performance data files. I keep only non-delinquent loans and loans with positive balances. I deflate the current loan balances using the BLS price index to obtain a measure of real loan balances, as at 1983. In total, there are approximately 17 million housing loans in the sample period of 2000-2007.

[80]One concern with self-reported data is that the data may be recorded with error. However, Einav, Leibtag and Nevo (2010) compare the self-reported data in Homescan with data from cash registers and conclude that the reporting error is of similar magnitude to that found in commonly used economic data sets.

[81]This data can be obtained from Freddie Mac (link here).

I identify a loan adjustment as all loans that enter the sample in the quarter, with a recorded purpose of "no-cash out refinance". Since the data is a loan panel-level, I focus on the loan adjustments that are due to "no cash-out" refinancing. These are transactions that are unlikely to involve a change in the loan balance on existing loans. This allows me to examine the correlations between loan adjustment propensities and loan size prior to the adjustment, without confounding any possible effects of loan balance increases due to "cash-out" activity. However, the results are also robust to considering "cash-out" refinancing. In Kirkman, Justiniano and Wong (2015), we examine other types of loan adjustments (cash-out refinancing and new homeownership) using the Equifax household-panel data. Since the Equifax data is at a household-level, we observe the loan balance immediately prior to the loan adjustment for all types of loan adjustments.

# B CPS Data

I use the quarterly CPS data over 1990-2007 to estimate the response of labor income and unemployment rate to monetary policy shocks. I construct synthetic cohorts based on age groups, educational attainment, and gender. I define the age groups based on 10-year age buckets. Educational attainment is defined based on three groups: college educated, high-school diploma or less than 2 years of post-high school education, and no high school diploma. These definitions ensure that there are at least 657 individuals within each group per quarter, and an average of 2,648 individuals per group-quarter.[82]

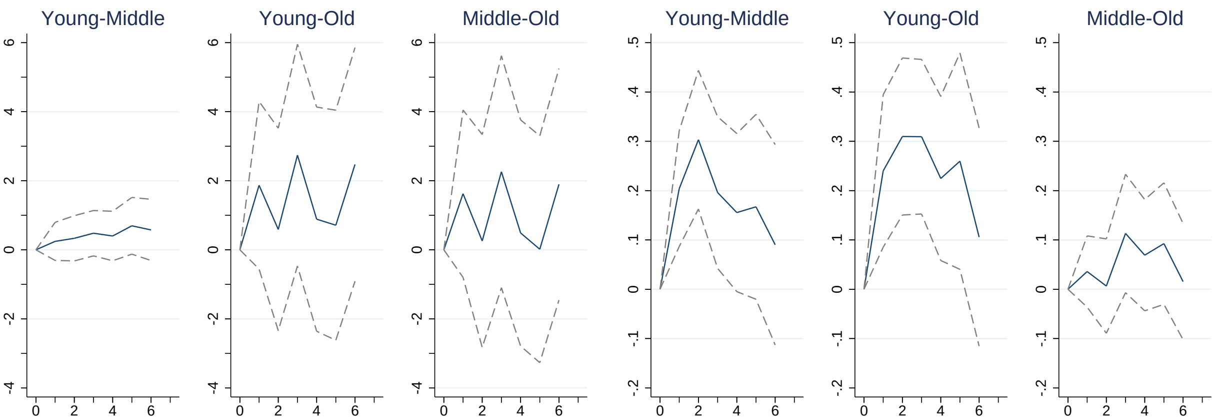
I regress the labor variables on expansionary and contractionary monetary policy shocks interacted with the age groups, controlling for age-education-gender fixed effects and a linear time trend. I consider two labor variables: log of weekly labor earnings, and the unemployment rate. [83] The estimated differences in labor responses by age group are depicted in Figure 8. There is some evidence that labor earnings of younger people change more than the labor earnings of middle-aged and older people (left panel of Figure 8. Most of the differences appears to be driven by the extensive margin of employment. The right panel of Figure 8 shows that a larger effect on the unemployment rate of younger people following an expansionary monetary policy shock. However, the magnitudes of the differences in the labor variables are much smaller than the differences observed for consumption. The differences are also statistically indistinguishable from zero. This implies that there are likely other channels, in addition to labor income, that have differential effects on consumption by age.

[82] I construct synthetic cohorts using the CPS rather than using the reported labor income in the CEX Survey. Unfortunately, the CEX survey only records information on income and employment at the second and fifth interview surveys for each household. The BLS then assumes that the labor variables remains unchanged between these interview dates, and pulls forward the data for the third and fourth interviews. Therefore, while examining changes in labor income at an annual frequency are well defined, examining labor income based on synthetic cohorts in the CEX survey at a quarterly frequency may be affected by changes in compositional mix of households rather than true changes in labor income each quarter.

[83] The time trend controls for any slow-moving structural changes to unemployment and earnings over the period. The results are qualitatively robust to other functional forms of the trend, such as year dummies and quadratic trends. To the extent that the information about the slow moving trends are already incorporated into the market rates on the Federal Funds futures contracts, then the measured monetary policy shocks will exogenous to these trends. Indeed, the inclusion or exclusion of these trend terms does not change the estimated labor elasticities in a statistically significant way.

Figure 8: Difference in the Effect on Earnings and the Unemployment Rate by Age

(a) Change in log of weekly earnings (b) Change in the unemployment rate




*Notes:* This table shows the labor earnings and unemployment rate response to a 1 standard deviation expansionary and contractionary monetary policy shock, based on Equation 5. 80 percent confidence intervals are depicted in parentheses. The elasticities are estimated using the CPS data.

# C Constructing age-specific price indices

Using the Nielsen data, I deflate total spending by age-specific price indices to focus on differences in life-cycle quantity response. The price indices are computed monthly. The approach is comparable to the BLS chained consumer price index approach.[84] Specifically, I compute the price index for individuals of age $a$ in period $t$ as:

$$P_t^a = P_{t-1}^a \times \frac{\sum_{i \in I} P_{it}^a \cdot q_{i,y(t)}^a}{\sum_{i \in I} P_{i,t-1}^a \cdot q_{i,y(t)}^a} \tag{21}$$

The price of a specific good $i$ (within the set of UPCs $I$) in month $t$ paid on average by individuals of age $a$ is denoted by $P_{it}^a$. It is computed as a quantity weighted average over all households $h$ of age $a$ (the set is denoted by $H(a)$):

$$P_{it}^a = \sum_{h \in H(a)} \sum_{w \in t} P_{hiw}^a \times \frac{q_{hiw}^a}{\sum_k q_{kiw}^a}$$

where $q_{hiw}^a$ denotes the quantity purchased in week $w$ within the month $t$.

The variable $q_{i,y(t)}^a$ in Equation 21 denotes the average monthly quantity of good $i$ purchased in year $y(t)$ by households of age $a$. It is computed as:

$$q_{i,y(t)}^a = \sum_{t \in y(t)} \sum_{h \in H(a)} \frac{q_{hit}^a}{H \times T}$$

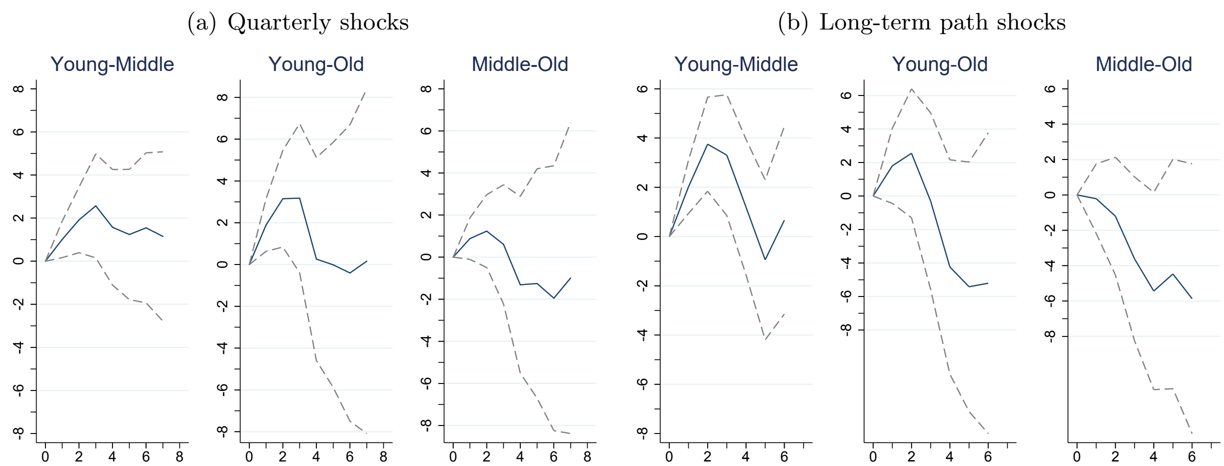
[84]Beraja and Vavra (2017) also follow a similar approach for constructing region-specific price indices using the Nielsen data.

This represents the weight on the price on each good $i$ in age-specific price index in Equation 21. The weight is fixed over all months within the year and is updated annually. An alternative approach would be to have the weights fixed over the entire sample. I find the results are qualitatively robust to the two approaches.

# D Consumption response to long-term shocks

The finding that consumption elasticities decline with age is robust to different measures of monetary policy shocks. The main results were based on a measure of the current period shock over the quarter. Below, I examine the consumption responses to long-term measures of a monetary policy shock. Figure 9 depicts the consumption response to a current period shock (left-hand panel) and to long-term "path" shock, based on the GSS decomposition (right-hand panel). I find that younger people adjust their consumption much more than middle-aged and older people under both measures of the shock. The heterogeneity in consumption responses is more pronounced for long-term shocks than the quarterly shocks. This may reflect the greater persistency of the long-term path shock on interest rates. Similar results can be seen with other measures of long-term shocks, such as the change in the two-year Treasury rate.

Figure 9: Difference in Non-durable Consumption Responses by Age Group




**Note:** This figure depicts the differential impulse response function to a 1 standard deviation expansionary monetary policy shock for the young relative to the middle (left panel), young relative to the old (middle panel), and middle relative to the old (right panel). The dashed lines depict the 80 percent confidence intervals.

# E Consumption response to future shocks

Table 14 below shows the estimated coefficients from a regression of the change in the log of consumption on forwards of the monetary policy shocks. This shows that consumption does not respond significantly to future measured shocks. To the extent that Federal Funds futures contracts are able to capture all current and past information available at the time of the shock, then we would not expect consumption to respond future measured shocks. This provides a useful test of the exogeneity of the shock.

Table 14: Forward Consumption Elasticities

| | Positive shocks | Negative shocks |
|---|---|---|
| T+4 | 0.98 | 1.80 |
| | [-3.05 , 5.01] | [-7.18 , 10.79] |
| T+3 | 0.04 | 1.89 |
| | [-3.07 , 3.15] | [-4.51 , 8.3] |
| T+2 | -0.79 | -2.12 |
| | [-3.2 , 1.62] | [-7.47 , 3.23] |
| T+1 | 0.30 | 2.69 |
| | [-1.37 , 1.98] | [-0.9 , 6.28] |
| T=0 | -0.27 | -0.58 |
| | [-1.26 , 0.73] | [-2.97 , 1.82] |

*Notes:* This table shows the forwards of the consumption response to a 1 standard deviation expansionary monetary policy shock that occurred at time T+k.

# F Contractionary monetary policy shocks

Table 15 below shows the consumption response to expansionary and contractionary monetary policy shocks, three quarters after the shock (the peak of the differential responses). The 90 percent confidence intervals are depicted in parentheses.

Table 15: Differences in Consumption Elasticities by Age

| | Young-Middle | Young-Old | Middle-Old |
|---|---|---|---|
| Expansionary shocks | 2.96 | 3.07 | 0.11 |
| | [0.41 , 5.51] | [-0.82 , 6.96] | [-3.24 , 3.46] |
| Contractionary shocks | 7.89 | 2.84 | -3.79 |
| | [-0.38 , 16.16] | [-6.71 , 12.38] | [-8.18 , 0.6] |

*Notes:* This table shows the average annual consumption response to a 1 standard deviation expansionary and contractionary monetary policy shock, based on Equation 5. 80 percent confidence intervals are depicted in parentheses. The elasticities are estimated using the CEX data.

# G Separating age from cohort effects

One concern we may have is whether the age-specific results reflect cohort effects, rather than life-cycle factors. The cohort effects refer to the birth year of the individual. For instance, it might be, in principle, that individuals born more recently react more strongly to recent shocks than individuals born more in the past.[85] If so, we may mistakenly think that the stronger response of people born more recently is due to a life-cycle effect related to age.

To show that my age-specific results hold, over and beyond the cohort effects, I re-estimate equation 5 with additional variables – specifically, the dummies for birth cohort group interacted with the contractionary and expansionary monetary policy shocks. The cohort groups are defined based on 20-year groups, starting from 1930. I consider 20 year periods to ensure there are sufficient households per cohort group.

Table 16 below shows the average annual consumption response by age to an expansionary monetary policy shocks, after controlling for birth cohort effects. The 80 percent confidence intervals are depicted in parentheses. As with the main results, the consumption response for total and non-durable consumption is declining with age.

Table 16: Differences in Consumption Elasticities by Age

| | **Young** 25-34 | **Middle** 35-64 | **Old** 65+ |
|---|---|---|---|
| Total | 6.78 | 3.28 | -0.58 |
| | [3.94 , 9.61] | [0.7 , 5.87] | [-3.63 , 2.48] |
| Non-durables | 2.65 | 2.45 | 0.89 |
| | [0.56 , 4.74] | [0.59 , 4.31] | [-0.65 , 2.43] |
| | **Young-Middle** | **Young-Old** | **Middle-Old** |
| Total | 3.49 | 7.35 | 3.86 |
| | [1.62 , 5.36] | [4.47 , 10.24] | [1.5 , 6.22] |
| Non-durables | 0.20 | 1.76 | 1.56 |
| | [-1.14 , 1.55] | [-0.59 , 4.1] | [-0.44 , 3.55] |

*Notes:* This table shows the average annual consumption response to a 1 standard deviation expansionary monetary policy shock, based on Equation 5. 80 percent confidence intervals are depicted in parentheses.

# H Loan adjustment by loan size

In this section, I examine the relationship between loan size and loan adjustment propensities using the Freddie Mac Loan Performance data, over the sample period 1999-2007. Specifically, I sort loans into decides. I estimate a probit model of a new loan regressed on lags of the monetary policy shock

[85]This could be rationalized by theories where expectations are updated based on a weighting of past life experiences. An older person has a longer period of time to average out the recent shock, and may therefore respond less. This is a very different theory from a life-cycle effect.

interacted with the loan size decile. The positive correlation between loan size and loan adjustment propensities is seen in Table 17.[86] The table presents the loan-adjustment propensities within the year of an expansionary monetary policy shock, by loan decile. Formally, I estimate

$$P_{ht} = b_0 + \sum_{k=1}^{K} \beta_k^a \cdot \epsilon_{t-k}^{-} + \sum_{k=1}^{K} \gamma_k^a \epsilon_{t-k}^{+} \cdot + \alpha X_{ht} + \lambda_{s(t)} + \nu_{ht}. \tag{22}$$

$X_{ht}$ denotes controls: loan age, credit score, indicator variables for MSA, and debt-to-income ratios.[87] The propensity to adjust the loan rises with loan size, ranging from 10% in the bottom decile to 48% in the top decile.

Table 17: Loan Adjustment Behavior by Loan Size

| Loan size decile | Propensity to adjust | Loan size decile | Propensity to adjust |
|---|---|---|---|
| 1 | 0.101*** | 6 | 0.279*** |
| | (0.001) | | (0.001) |
| 2 | 0.168*** | 7 | 0.286*** |
| | (0.001) | | (0.001) |
| 3 | 0.234*** | 8 | 0.307*** |
| | (0.001) | | (0.001) |
| 4 | 0.228*** | 9 | 0.316*** |
| | (0.001) | | (0.001) |
| 5 | 0.253*** | 10 | 0.479*** |
| | (0.001) | | (0.002) |

*Notes:* This table shows the average annual propensity to adjust a loan (given the household owns a home) by quintile of loan size. Q1 and Q10 denote the smallest and largest 10% of loans in the loan size distribution, respectively. The standard errors are in parentheses and the 1, 5, and 10 percent significance levels are denoted by $***$, $**$, and $*$ respectively. The propensities are estimated using the Freddie Mac Loan Performance micro data, which spans 2000-2007. See text for more details.

# I State-level Consumption Elasticities

An alternative approach to understanding the effect of demographics on the aggregate consumption response is to examine the responses across regions in the U.S. In this section, I present evidence that the aggregate consumption in states with a younger demographic structure responds more to interest rate shocks, consistent with the household-level findings.

[86] As discussed in Section 2, I focus on no cash-out refinancing loan adjustments, when looking at loan balances, since loan balances are tracked over time at the loan-panel level rather than the household-level. However, the results are also robust to the inclusion of "cash-out" refinancing. In Kirkman, Justiniano and Wong (2015), we examine other types of loan adjustments (cash-out refinancing and new homeownership) using the Equifax household-panel data.

[87] These propensities are estimated based on Equation 22 using the Freddie Mac Loan Performance data over the sample period 2000-2007, and controls for the household's credit score, leverage (debt-to-income and debt-to-valuation ratios) and loan age. See Section 2 for more detail on the data construction. I further explore the effects of these demographic variables in Justiniano et al. (2012), using Equifax data. The results, based on the Equifax data, are consistent with the findings based on the Freddie Mac Loan Performance data.

To investigate the regional variation in consumption responses, I estimate:

$$\triangle \ln C_{ht} = b_0 + \sum_{k=1}^{K} \beta_k \cdot \epsilon_{t-k} + \sum_{k=1}^{K} \alpha_k \cdot \epsilon_{t-k} \cdot P_{r(h),t-k} + \sum_{k=1}^{K} \gamma_k \cdot \epsilon_{t-k} \cdot S_{r(h),t-k} + \lambda_s(t) + \theta' Z_{ht} + \nu_{ht} \quad (23)$$

for household $h$ in quarter $t$ living in states $r$, and $K = 9$ quarters. $P_{r(h),t}$ denotes the share of old to young in region $r$ (where the old and the young are defined as those aged over 65 and those between 25 and 35 year of age, respectively). $S_{r(h),t}$ is a vector of state-level variables that can affect the local area consumption response. These include the sectoral composition and local area housing supply elasticity.[88]

The term

$$\beta_k + \alpha_k \cdot P_{r(h),t} + \gamma_k \cdot S_{r(h),t}$$

gives the change in the growth rate of consumption $k$ periods after an initial shock at time $t$. The consumption elasticity after $T$ periods for region $r$ is:

$$\left.\frac{\partial \ln C_{h,t+T}}{\partial \epsilon_t}\right|_r = \sum_{k=1}^{T} \left.\frac{\partial \triangle \ln C_{h,t+k}}{\partial \epsilon_t}\right|_r = \sum_{k=1}^{T} \left[\beta_k + \alpha_k \cdot P_{r(h),t-k} + \gamma_k \cdot S_{r(h),t-k}\right] \quad (24)$$

The effect of the local area population structure on the local area consumption elasticity, relative to the national average response, is given by

$$\sum_{k=1}^{T} \alpha_k \cdot P_{r(h),t} - \sum_{k=1}^{T} \alpha_k \cdot P_{U.S.,t} \quad (25)$$

where $P_{U.S.,t}$ denotes the national young-old ratio.

I estimate Equation 23 using the Nielsen Homescan data since has a broad geographic coverage of household food consumption in U.S. The estimated coefficients are given in Table 18. See Section 4 for more detail and discussion.

[88] As shown in Mian and Sufi (2014) and Mian, Rao and Sufi (2013), the local area housing supply elasticity is highly correlated with refinancing decisions.

Table 18: State-level Consumption Elasticities to Interest Rate Shocks

| Variable | Coefficient | Standard deviation |
|---|---|---|
| $\epsilon_{t-1}$ | -0.2*** | (0.07) |
| $\epsilon_{t-2}$ | -0.08 | (0.064) |
| $\epsilon_{t-3}$ | 0.097** | (0.044) |
| $\epsilon_{t-4}$ | -0.032 | (0.039) |
| $\epsilon_{t-5}$ | -0.233*** | (0.035) |
| $\epsilon_{t-6}$ | -0.059* | (0.036) |
| $\epsilon_{t-7}$ | -0.071** | (0.031) |
| $\epsilon_{t-8}$ | 0.058** | (0.03) |
| $\epsilon_{t-9}$ | -0.159*** | (0.031) |
| $\epsilon_{t-1} \cdot P_{r(h),t-1}$ | 0.721** | (0.291) |
| $\epsilon_{t-2} \cdot P_{r(h),t-2}$ | 1.561*** | (0.27) |
| $\epsilon_{t-3} \cdot P_{r(h),t-3}$ | -0.284 | (0.189) |
| $\epsilon_{t-4} \cdot P_{r(h),t-4}$ | 0.016 | (0.172) |
| $\epsilon_{t-5} \cdot P_{r(h),t-5}$ | 1.184*** | (0.153) |
| $\epsilon_{t-6} \cdot P_{r(h),t-6}$ | 0.402*** | (0.157) |
| $\epsilon_{t-7} \cdot P_{r(h),t-7}$ | 1.468*** | (0.134) |
| $\epsilon_{t-8} \cdot P_{r(h),t-8}$ | 0.057 | (0.125) |
| $\epsilon_{t-9} \cdot P_{r(h),t-9}$ | -0.091 | (0.125) |

*Notes:* This table gives the coefficients estimated from Equation 23, which regresses the change in the log of consumption for the household in period $t$ on lagged values of the monetary policy shocks $\epsilon$ and interactions of the lagged values of the monetary policy shocks with the share of old to young in region $r$. Standard errors are given in parentheses. ***, **, and * denotes significance at the 1, 5 and 10 percent level, respectively.

## I.1 Computational Appendix

In this section, I describe the solution to the model described in the body of the text. In order to implement the solution to this model numerically, I proceed as follows.

First, I reformulate the choice variables to rectangularize the problem and simplify computational issues that arise from the endogenous mortgage constraint. I reformulate the problem in terms of the leverage ratio, defined as

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

I substitute the budget constraint into the utility function to eliminate consumption as a choice variable. The choices variables are therefore $s_{jat}, h_{jat}, 1(\text{rent})_{jat}, 1(\text{adjust})_{jat}, q_{jat}$. I then discretize the problem so it can be solved on the computer. I discretize the idiosyncratic income variable $y_{jat}$ and multivariate aggregate state vector $S_t = [y_t, \log p_t, r_t]$ using the algorithm of Tauchen (1986). I then simulate the quarter process of $S_t$ to get the annual probability transition matrix for $S_t$. I use 18 grids for $S_t$ and four grids for $y_{jat}$. I approximate the value functions ($V_j^{\text{own \& noadjust}}(z_{jat})$, $V_j^{\text{own \& adjust}}(z_{jat})$ and $V_j^{\text{rent}}(z_{jat})$) as multilinear functions in the states, where $z_{jat} = [S_t, y_{jat}, \text{assets}_{jat}]$. There are four endogenous states $\text{assets}_{jat} = \left[s_{jat}, h^o_{jat}, b_{jat}, r_{jat}\right]$. I use 20 knots for $h^o_{jat}$ and $b_{jat}$ and 10 knots $s_{jat}$ and $r_{jat}$. The knots are spaced more closely together near the constraints for $b_{jat}$ and $s_{jat}$. I assume multilinear interpolation of the value functions between the knots.

I solve the model by backward induction from the final period of life. At each age and each case, I compute optimal policies using a Nelder-Meade algorithm. I compare the value functions for each of the three cases (to rent, to own a home and adjust the mortgage, to own a home and not adjust the mortgage) to generate the overall policy function. In order to compute the impulse response functions and the life-cycle moments, I simulate a panel of $10,000$ households (100 cohorts) over their life-times.

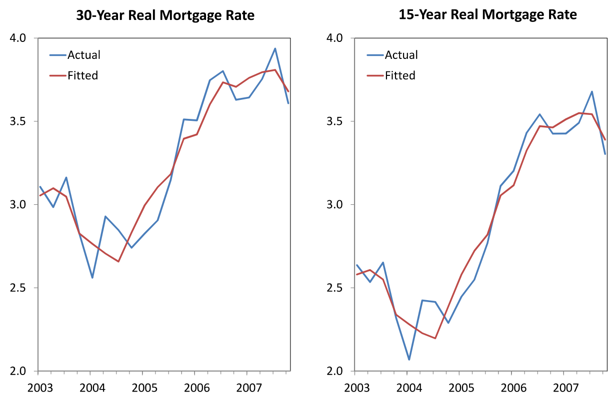
To compute the impulse response functions of consumption to a monetary policy shock, I first simulate the consumption and asset profiles decisions for 100 different cohorts, with 1000 households in each cohort. Each cohort faces a different historical path for the state variables. Second, for each cohort, I compute the consumption choice for each household following a monetary policy shock. This involves feeding in the aggregate dynamics following the shock for house prices, rental rates, interest rates, mortgage rates, and income, and computing the consumption choices. Third, I compare the consumption response under the monetary policy shock to the consumption choice that would have occurred if the households faced the aggregate dynamics under no monetary policy shock. Fourth, I aggregate up across households within the same cohort, assuming the demographic profile of the economy, to compute the aggregate consumption response and take the average across cohorts.

## I.2 Mortgage Rate, House Prices and Rental Rates

In the model, I specify linear approximations of the mortgage yield curve, house prices and rental rates as a function of aggregate state variables. The mortgage yield curve is a function of the short-term interest rate, and aggregate employment. House prices and the house price to rent ratios are a function of prior period house price, short-term interest rates, and aggregate employment. One advantage of specifying these processes in this way is that it generates plausible time series and impulse response function dynamics, without adding additional state variables to the computation.

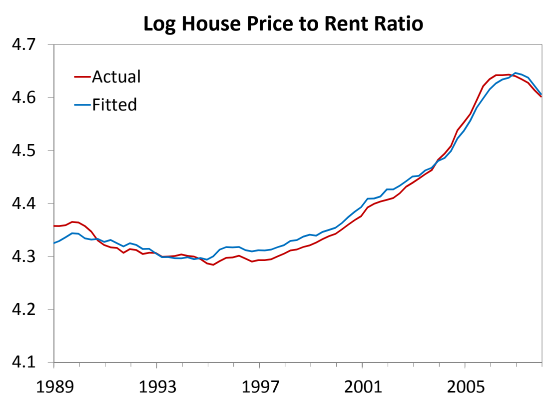
In this section, I provide evidence that the linear specifications are indeed good approximations of actual dynamics. Figure 10 shows that the predicted 30- and 15-year real mortgage rates closely fit the actual mortgage rates over time. Figure 11 also show that the predicted and actual log house price to rent ratios are similar over time.

Figure 10: Predicted and actual 30-year mortgage rate




*Notes:* This figure depicts the model predicted and actual 30- and 15-year real mortgage rates.

Figure 11: Predicted and actual log house price to rent ratio




*Notes:* This figure depicts the model predicted and actual log house price to rent ratio. The latter is from the St Louis Federal Bank.