Consumer Spending and Aggregate Shocks

by

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Dedication

This dissertation is dedicated to my parents Mingxian Zhao
and Anhua Zhou.

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ABSTRACT

Consumer spending is widely considered to be the engine that drives economic growth and prosperity. This dissertation employs theoretical, empirical and computational methods to study the interaction between consumer decisions at the microeconomic level and the evolution of consumption at the macroeconomic level.

Chapter 1

This paper provides a unified account of the U.S. consumption and residential investment dynamics over the last 15 years. Conventional wisdom holds that the consumption boom-bust cycle of the 2000s was caused by homeowners financing their consumption through home equity extraction. However, most of the funds extracted by homeowners are spent on home improvement rather than consumption. This association is strongest among young households. I rationalize these findings using a life-cycle model with home equity-based borrowing subject to borrowing frictions. Over a household's life cycle, the model generates lumpy housing investment associated with infrequent equity extractions, especially at the early stages of the life cycle. The model further implies that shocks in the housing

market, such as an unexpected increase in house prices or a mortgage rate reduction, cause homeowners, who otherwise would not extract equity, to extract and to spend disproportionately on their homes. The boom-bust cycles in consumption and residential investment implied by this model capture several key features of the corresponding cycles found in U.S. data. The model provides a more subtle explanation of the role played by home equity extractors in the consumption cycle. Although extractors individually spent only a small fraction of their extracted funds on consumption, they collectively accounted for much of the consumption boom because the share of extracting households increased rapidly in the early 2000s.

Chapter 2

Can government spending have a large effect on private consumption and income? This paper uses a novel dataset on federal government disaster-relief spending, combined with both household and state-level consumption, income and employment data, to answer this question. My estimates show that the demand shock created by government disaster-relief spending can have a large multiplier effect, and that this effect comes from the government's influence on the labor market. I show that, in states receiving disaster-relief spending from the federal government, households who are most likely to work for disaster-relief related jobs have the largest consumption growth. When a state receives such spending, the industries in this state that provide most disaster-relief related jobs experience the largest employment growth. My findings are supportive of the job-creation channel emphasized in New Keynesian models of the transmission of government spending shocks.

Chapter 3

The Housing Provident Fund program is the largest public housing program in China. It was created in 1999 to enhance homeownership and to make housing more affordable. This program involves a mandatory savings scheme that requires participating workers to deposit a fraction of their income into the program. Past deposits are refunded when the worker purchases a house, or retires. The program provides mortgages at subsidized rates to facilitate these home purchases. Given the empirical challenges in evaluating the success of this program, I use a calibrated life-cycle model to quantify the effectiveness of these polices. My analysis shows that a housing program with these features is expected to increase the rate of homeownership by 4 percentage points in steady state. In addition, the average home size increases by 21% relative to the baseline model. These results are largely unaffected by the existence of employer contributions. I discuss the economic mechanisms by which these outcomes are achieved.

CHAPTER 1

Home Equity Extraction and the Boom-Bust Cycle in Consumption and Residential Investment

1.1 Introduction

Between 2000 and 2013, the U.S. economy experienced large, cyclical fluctuations in consumption and residential investment. For example, the annual growth rate of real personal consumption expenditures was about 3 percent before 2007, fell below zero during the financial crisis in 2008 and 2009, and then recovered to 1.8 percent after 2009. In retrospect, many academics and policy analysts have pointed to easily available credit and cash extracted from home equity as a likely explanation for this consumption boom-bust cycle.[1] The conventional argument is that before the crisis, homeowners were able to obtain cash from lenders by using their houses as collateral and used this cash to finance their consumption. During the crisis, this borrowing channel dried up and consumption fell. This explanation is difficult to reconcile with microeconomic data, however, because household-level surveys suggest that home improvement spending, not consumer good purchases, appears to be the most important use of the extracted funds.[2] For example, Canner et al. (2002) find that 35 percent of extracted home equity is spent on home improvements, in contrast to 16 percent on all other consumer expenditures.

In this paper, I propose an alternative account of the consumption boom-bust cycle that is consistent with both the microeconomic and macroeconomic evidence. My analysis provides a unified explanation of U.S. private consumption and residential investment

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[1]Examples include Mian and Sufi (2011), Mian et al. (2013), Mian and Sufi (2014), and Bhutta and Keys (2016).

[2]Improvements to residential structures are recorded as residential investment in the NIPA accounts. They consist of: (i) additions and alterations, such as the addition of another floor to an existing house, the finishing of basements and attics, the remodeling of kitchens or bathrooms, and the addition of swimming pools or garages, and (ii) major replacements such as new roofs, water heaters, furnaces and central air conditioners. These expenditures prolong the life of the structure or add to its value. Routine maintenance and repair work are excluded.

expenditures over the last 15 years. I identify the theoretical mechanisms responsible for the cyclical fluctuations in these expenditures. Building on Berger et al. (2015), I construct a structural life-cycle model motivated by household-level evidence. A calibrated version of this model captures several key features of the cycles found in U.S. data. The model shows that the rapid increase in the share of extracting households in the early 2000s explains much of the consumption boom, even though individual extractors spent only a small fraction of extracted funds on consumption.

The choice of this structural model is motivated by empirical evidence, some of which is well established and some of which is new. In Section 1.2, I document several empirical correlations in the Panel Study of Income Dynamics (PSID), a nationally representative panel dataset at the household level. First, I document a high positive correlation between the decision to extract home equity and the decision to make substantial home improvement expenditures.[3] In addition, I show that this correlation is largest among young homeowners. This fact has not been recognized in the existing literature and is essential for designing a model to explain this correlation and for studying the aggregate implications for household-level behavior. Second, I compare the expenditure growth of equity extractors and non-extractors. I find that extractors have significantly higher housing expenditure growth than non-extractors. This difference is most pronounced among young homeowners. These correlations are robust to controlling for time fixed effects, designed to capture aggregate time trends, and to controlling for changes in one's house price. Third, I use a restricted version of the PSID data that provides detailed geographic information on households, combined with Metropolitan Statistical Area (MSA) level house price movements, to identify exogenous house price shocks. Using these data, I demonstrate that positive house price shocks stimulate equity extraction. Furthermore, young homeowners are most responsive to these shocks. In the remainder of the paper, I show how these three empirical results can be explained by a model with home equity-based borrowing and borrowing frictions.

In Section 1.3, I adapt the consumption life-cycle model of Berger et al. (2015) to study the importance of borrowing frictions in explaining the demand for home equity and housing investment. The model explains why it is optimal for homeowners to spend largely on housing when tapping their home equity.[4] The model has two consumption

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[3]This paper is not the first to document such a correlation in the data. The correlation in question, in fact, is robust across sample periods, across different data sources and across countries (see, e.g., Greenspan and Kennedy (2007), Canner et al. (2002), Brady and Maki (2000),Cooper (2009), Nam (2015), Benito and Power (2004), and Smith (2010)).

[4]This result differs from the standard consumption models incorporating home equity as an illiquid asset. These models imply that households extract home equity to smooth their non-housing consumption over time (see, for example, Hurst and Stafford (2004), Beraja et al. (2015), Kaplan and Violante (2014), and Li

goods: housing and non-housing. I allow households to save in three ways: by increasing liquid assets, by paying down mortgage debt, and by investing in housing. Unlike in the standard incomplete markets model, households are allowed to use their houses as collateral to borrow, but the borrowing cannot exceed the value of the house. Additionally, collateral borrowing is subject to frictions due to mortgage adjustment costs. As a result, equity extractors pay fixed costs for extracting cash up to the collateral value, and non-extractors repay according to their original mortgage terms. The model is calibrated to the U.S. data.

Over the life-cycle of a household, the model generates lumpy housing investment associated with infrequent equity extractions, especially among young households. This pattern exists even in the steady state when house prices and interest rates are constant. The intuition behind this pattern is as follows. Housing generates utility. Young households start their life with small houses, which means that the marginal utility of housing consumption is high, so they want to invest in housing. However, young households are liquidity constrained, so in order to invest in their homes, they must borrow against their home value. Borrowing frictions prevent them from changing their borrowing continuously. As a result, households extract equity only occasionally, and when they do, they remove a chunk of cash and invest it in housing. The key structural assumptions that generate the positive correlation between equity extraction and housing investment expenditures are (a) the fact that housing serves both as a consumption good and as a collateral asset, (b) the existence of liquidity constraints, and (c) the presence of borrowing frictions.

I then show that this behavior is amplified by shocks in the housing market which move the economy away from its steady state. For example, an unexpected increase in the house price, or an unexpected reduction in the mortgage rate, causes homeowners to extract equity sooner than planned, and to spend this equity on housing. Therefore, homeowners' spending on housing, especially by young home equity extractors, is the key to understanding the aggregate response of consumption and residential investment to shocks in the housing market.

To illustrate the aggregate implications of the model for consumption and residential investment, I quantify the impact of several shocks including unexpected house price changes and mortgage rate reductions. Unlike the previous literature, I distinguish between shocks to the house price (or, equivalently, to the value of housing collateral), and shocks to the cost of improving and building homes. I show that an unexpected increase in house prices raises both housing and non-housing expenditures by relaxing the collateral constraint. In contrast, an unexpected increase in the cost of improving and building homes lowers housing expenditures and increases non-housing expenditures due to a combination

(2009)).

3

of the income, substitution and wealth effects. An unexpected reduction in the mortgage rate has roughly the same qualitative effect as an unexpected increase in house prices. The key difference is that a lower mortgage rate does not increase the available home equity immediately. Therefore, the impact responses of housing and non-housing expenditures are not monotonically declining with age. Instead, they peak among young-to-middle-aged households, who are liquidity constrained and have substantial equity accumulated in their houses. For each of the three shocks, the response of housing expenditures is much larger than non-housing expenditures.

As noted earlier, extractors spend more on housing than non-extractors. This result does not tell us, however, what the contribution is of extractors and non-extractors, respectively, to the residential investment in response to shocks in the housing market. The structural model sheds light on this question. In the model, almost all the effect of unexpected house price or mortgage rate changes on residential investment is driven by the housing expenditures of extractors, with a disproportionate contribution made by young extractors.

Before using the model to understand the mechanism behind the boom-bust cycle in consumption and residential investment, it is important to assess the ability of the model to explain the evolution of consumption and residential investment in the U.S. economy during the 2000s. For this purpose, I simulate the evolution of these variables after feeding into the model historical real house prices, real home construction cost indexes, and real mortgage rates. I then compare the simulated data to the actual U.S. data. I show that the model captures several key features of the boom-bust cycles found in the U.S. data during this period.

The economic explanation of these cycles is that during the boom, as house prices increased and mortgage rates declined, the aggregate housing stock was built quickly due to the investment made by home equity extractors. The growing housing stock facilitated more home equity-based borrowing which in turn financed spending on both housing and non-housing expenditures. In the subsequent bust period, when house prices fell sharply, fewer households extracted equity. As a result, housing investment declined and the collateral value shrank, further dampening equity extraction and aggregate spending.

The explanation of the boom-bust cycle in residential investment in this model is straightforward. The explanation of the consumption boom-bust cycle is more subtle, given that each household spends only a small fraction of extracted equity on non-housing expenditures. The consumption boom-bust cycle arises not because there is a direct link from home equity-based borrowing to consumption at household level, as commonly presumed, but because the share of equity extractors increased dramatically from 5 percent in 2000 to 50 percent in 2005, before dropping back to 10 percent after 2007.

The remainder of the paper is organized as follows. Section 1.2 describes the features of the data that motivate the theoretical analysis. Section 1.3 discusses the model, and Section 1.4 describes its calibration. In Section 1.5, I discuss the optimal life-cycle choices in steady state and show that the model explains the empirically observed correlations between equity extraction and housing investment expenditures. Section 1.6 studies the responses of the economy to shocks in the housing market. Section 1.7 assesses whether the calibrated model can explain the boom-bust cycle in consumption and residential investment between 2000 and 2013. Section 1.8 concludes.

1.2 Empirical Evidence

In this section, I present three empirical findings that in conjunction motivate the theoretical analysis in Section 1.3. First, I document a high correlation between the decision to extract home equity and the decision to make substantial home improvement spending. This correlation is largest among young homeowners. Second, comparing the expenditure growth of equity extractors and non-extractors, I find that extractors have significantly higher housing expenditure growth than non-extractors. This difference is again most pronounced among young homeowners. Third, I show that positive house price shocks stimulate equity extraction, with young homeowners being most responsive to these shocks.

1.2.1 Data and Sample Selection

My primary data source is the Panel Study of Income Dynamics (PSID) biennial family survey and its supplemental files on consumption for 1999 to 2013. The PSID sample is representative of the U.S. population and provides detailed information on household wealth, mortgage conditions, income and expenditures under a multi-year panel structure, allowing me to link consumer spending to mortgage borrowing.[5] I apply the following sample selection criteria. First, I exclude renters and homeowners without mortgages.[6]

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[5]There are few large household panel datasets that track the distribution of wealth, income and consumption simultaneously. The PSID dataset used in this paper is one of two surveys studying U.S. households. Another is the Consumer Expenditure Survey (CE), which provides detailed measures of spending, but not of income or the household balance sheet, so changes in spending cannot be directly traced to changes in mortgage borrowing. In addition, the short panel structure of the CE limits the scope for studying income and wealth dynamics.

[6]There are two reasons for excluding homeowners without mortgages in the baseline estimation. First, homeowners without mortgages tend to be richer, older, and tend to have more liquid wealth, and hence less likely to extract home equity. This makes them different from homeowners who have mortgages but choose not to extract equity. Since I want to compare homeowners of similar financial conditions, I exclude those without mortgages. Second, homeowners without mortgages are in general not qualified for refinancing. Nevertheless, it can be shown that the results of my analysis are robust to including all homeowners.

Second, I select homeowners that have not moved for at least two interviews.[7] Third, I drop families owning farms or businesses because their equity extraction may be highly correlated with their business investment. Fourth, I exclude families with negative total income or a home value below \$200. Finally, I drop homeowners younger than 22 or older than 75. Following Bhutta and Keys (2016), I identify home equity extraction in the data as incidents when the homeowner's total mortgage balance increases by more than 5 percent between two interviews, and the increase exceeds \$1,000. By this definition, equity extraction could take the form of cash-out refinancing, taking a second mortgage, or acquiring a home equity line of credit.[8]

Table 1.1 shows the average mortgage balance of U.S. households as defined above, the average of their self-reported home value, the equity extraction rate, and the frequency of cash-out refinancing as an extraction method in the PSID data between 1999 and 2013. Whereas average mortgage balances increase over time, home values experience a boom-bust cycle similar to the national house price index (see Section 1.7). Home equity extraction is popular between 2001 and 2007 with cash-out refinancing being the most frequently used method.

Tables 1.2 and 1.3 document that home equity extractors, although not systematically different from non-extractors based on their demographic characteristics, show different financial characteristics. In Table 1.2, the demographic characteristics of home equity extractors and non-extractors are shown to be similar. Table 1.3 summarizes the financial conditions of current equity extractors in the current and the previous interview. In the previous interview, the two groups have similar income, total wealth and expenditures, but the extractors have a larger fraction of their wealth in home equity, and have lower liquid assets than non-extractors. In the current interview, extractors have less total wealth and less home equity, but they have a larger growth in housing expenditures than non-extractors.

1.2.2 Equity Extraction and Housing Expenditures

Pooled OLS regressions reveal three additional facts of interest. First, the decision to extract home equity is highly correlated with the decision to make substantial home improvement expenditures. Second, extractors have significantly higher housing expenditure growth than non-extractors, but their expenditure growth in other consumer

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[7]Movers are excluded by this restriction because moving is usually associated with other permanent shocks such as job changes, retirement, and family reasons. Results are robust to including movers because the moving rate for homeowners is only 10 percent over a two-year interval.

[8]Since cash-out refinancing is the most common way to extract home equity, and refinancing is reported in the survey, I also conduct the same analysis restricting equity extraction to cash-out refinancing. The results are very similar.

goods is not significantly different from non-extractors. Third, both of these tendencies are most pronounced among young homeowners.

Extensive Margin Correlation   Since 1984, the PSID has asked questions regarding the spending on home improvements and additions that exceed $10,000. Both spending decisions and the actual amount are reported. To see how robust the correlation between equity extraction and improvement spending is, I plot the fraction of households making substantial improvement among home equity extractors and non-extractors in Figure 1.1.[9] The figure shows that extractors are more likely to make large improvement expenditures than non-extractors in almost all years, not only during the housing boom period of 2000 to 2005.[10] This average difference may be deceiving, however, to the extent that extractors are young households short of cash and living in small houses, and non-extractors are old, rich households who do not need further home improvement.

Regression analysis helps to control for these characteristics. Consider the regression model,

$$I(Improvement)_{i,t} = \alpha_0 + \alpha_1 I(Extract)_{i,t} + X_{i,t}\alpha_2 + W_{i,t-1}\alpha_3 + \gamma_t + \varepsilon_{i,t} \qquad (1.1)$$

where $I(Improvement)_{i,t}$ is an indicator of household i at time t making substantial home improvements or additions exceeding $10,000, and $I(Extract)_{i,t}$ is an indicator of household i extracting equity at time t. $X_{i,t}$ is a vector of changes in income and in home values. $W_{i,t-1}$ is a vector of financial conditions including the previous period income, liquid and illiquid assets. γ_t is a set of year dummies, designed to capture aggregate time trends, such as changes in interest rates and business cycle fluctuations.

Table 1.4 reports results across various specifications. Column (1) shows that home equity extractors are 7 percent more likely to make substantial home improvement than non-extractors. Column (2) shows a similar result when including the previous financial conditions. Column (3) controls for the time fixed effects, column (4) controls for the growth rate of one's home value, and column (5) further controls for the household fixed effects. Results from the last three columns show that even in the absence of aggregate time trends and changes in one's house price, home equity extractors are still more likely

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[9]The reason I focus on home improvement expenditures is that this type of residential investment expenditures is precisely measured in the PSID data, whereas the value of acquisition of houses is not, in that households only report estimates of their home value, not actual transaction prices.

[10]In the 2013 survey, this difference shrinks because fewer households extracted home equity, so the fraction of households making substantial improvement among extractors could be imprecisely measured. The low extraction rate in 2013 might be explained by the passing of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank). A main theme in Dodd-Frank is to emphasize the ability to pay through verifying a number of underwriting factors, which discourages risky lending (see Bhutta and Ringo (2015)).

to make large home improvement expenditures.[11]

Model (1.1) may also be estimated separately for different age groups. Table 1.5 shows that the correlation between equity extraction and home improvement is largest among young households, implying important heterogeneity across households. Of homeowners aged between 22 to 30, extractors are 18 percent more likely to make substantial home improvement expenditures than non-extractors.[12]

Intensive Margin Correlation   I now compare the relative expenditures on housing and non-housing between home equity extractors and non-extractors.[13]   To remove household fixed effects, I focus on expenditure changes and estimate the regression model

$$\frac{\triangle c_{i,t}^k}{c_{i,t-1}^{tot}} = \beta_0 + \beta_1 I(Extract)_{i,t} + X_{i,t}\beta_2 + W_{i,t-1}\beta_3 + \gamma_t + \varepsilon_{i,t} \qquad (1.2)$$

where $\triangle c_{i,t}^k$ denotes the change in expenditures of a specific category k (total, housing, non-housing). $c_{i,t-1}^{tot}$ denotes the total expenditures in the previous period. All dollar amounts are converted to 2009 dollars. β_1 measures the difference in expenditure growth between equity extractors and non-extractors.[14]

Column (1) in Table 1.6 shows that the total expenditure growth of equity extractors is 10 percentage points higher than non-extractors. I then decompose total expenditures into non-housing expenditures (food, transportation, education, childcare and health), and housing expenditures (property tax, insurance, utilities, home improvement and mortgage payment). Columns (2) and (3) show that the difference in the total expenditure growth mainly comes from the expenditure growth in housing, which accounts for a difference of 8 percentage points, rather than the expenditure growth on other consumer goods. To remove the expenditure growth driven by higher mortgage payment, columns (4) and (5) show the results for housing expenditures excluding mortgage payment, and for home improvement, respectively. Column (4) shows that excluding mortgage payment, the housing expenditure

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[11]For expository purposes, Table 1.4 reports OLS estimates of model (1.1). Very similar results are obtained when I estimate a probit version of model (1.1), and compute the average partial effect of equity extraction on home improvement.

[12]I also find a weak correlation between equity extraction and investment on other real estate, with the highest correlation appearing for age 65 and above. However, these results are not robust. I do not find that equity extraction is positively correlated with other investments such as stocks or retirement savings.

[13]To maximize the sample size, I use the PSID expenditure data since 1999. These expenditures include food, housing, transportation, education, childcare and health, covering 70 percent of total expenditures measured in the Consumer Expenditure Survey (CE), according to Li et al. (2010).

[14]I divide the change in housing and non-housing expenditures by the previous period's total expenditures, rather than constructing their own growth rate, because housing expenditures for some households are zero in the data. In the following analysis I use expenditure growth to refer to the change in expenditures divided by the previous period's total expenditures.

growth of extractors is 4.6 percentage points higher than non-extractors, explaining 60 percent of the difference in the housing expenditure growth. Column (5) further shows that home improvement explains almost all the difference in the housing expenditure growth after excluding mortgage payment.[15]

Table 1.7 shows the results from estimating model (1.2) by age group. Again, I find substantial heterogeneity. The difference in housing expenditure growth declines with age. The housing expenditure growth of extractors aged 22 to 30 is 17 percentage points higher than for similarly aged non-extractors. Table 1.8 shows a similar life-cycle pattern in the housing expenditure growth when excluding mortgage payment. Table 1.9 shows that the non-housing expenditure growth does not differ much between extractors and non-extractors in any of the age groups.[16]

1.2.3 House Price Shocks and Equity Extraction

Of particular interest for the theoretical analysis in Section 1.3 is the question of how households respond to unexpected changes in house prices.[17] This question may be addressed based on the regression model

$$I(Extract)_{i,t} = \theta_0 + \theta_1 \triangle hp_{i,t} + \theta_2 \triangle y_{i,t} + W_{i,t-1}\theta_3 + \gamma_t + \varepsilon_{i,t} \tag{1.3}$$

where $\triangle hp_{i,t}$ denotes the percent growth in household i's self-reported home value from period $t-1$ to t. The regression controls for income growth $\triangle y_{i,t}$ and the previous period's financial conditions, $W_{i,t-1}$, as defined in model (1.1).

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[15]In related work, Cooper (2009), using the 1999-2009 PSID data, investigates the spending of the marginal dollar extracted from home equity. His estimates are not comparable across spending categories or years, however. For example, in estimating spending on home improvement, he drops all households making zero improvement that correspond to 90 percent of the sample (Table 5 in his paper), which results in an overestimate of the home improvement spending. In Appendix A.1, I perform marginal dollar spending analysis on housing and non-housing expenditures that is comparable across spending categories and age groups. My results show that housing expenditures account for a much larger fraction than all other expenditures, and young households spend largest fraction of the marginal dollar on housing.

[16]Two further robustness checks are provided in Appendix A.1. First, since the PSID expenditure data from 1999 used in the previous analysis may not capture the full scope of spending, I run the same analysis using the PSID expanded expenditure data from 2005 onwards, which, according to Andreski et al. (2014), capture almost all expenditures measured in the CE. Second, I estimate the spending of a marginal dollar extracted from home equity, and provide age-specific estimates. The results show that a marginal dollar extracted is mostly spent on housing and such spending is largest among young extractors.

[17]Although the responses of households to unexpected mortgage rate changes would be interesting to empirically study as well, there is not enough variation in the mortgage rate over my sample to reliably estimate that response. The reason is that the PSID data are biennial. This problem does not arise in studies based on quarterly data, such Bhutta and Keys (2016) and Wong (2015). The latter studies, of course, do not have the detailed data required to answer the questions of interest in the current paper.

In the baseline specification, I treat the percent growth in the household's self-reported home value as a measure of the house price shock and estimate model (1.3) by OLS. Column (1) in Table 1.10 shows that, on average, a 1 percent home value appreciation leads to a 0.13 percentage point increase in the probability of extracting home equity. The remaining columns show that young households are most sensitive to house price shocks in extracting home equity.

It is possible that equity extractors tend to report higher home value after making home improvements, or that, individual characteristics may cause extractors to be overly optimistic about their own home value. Hence, changes in households' self-reported home value may be endogenous to home equity extraction in model (1.3). To allow for these possibilities, I also consider an instrumental variable estimation approach. I rely on two alternative sets of instruments, both of which are constructed using detailed geographic information from the PSID data.

The first set of instruments is the change in the Metropolitan Statistical Area (MSA) level house price index published by the Federal Housing Finance Agency (FHFA). The identification assumption is that, conditional on household characteristics, regional controls and time fixed effects, MSA level housing market performance is unaffected by individual household equity extraction decisions. I perform 2SLS estimation using this set of instruments in the first stage to estimate

$$\triangle hp_{i,t} = \phi_0 + \phi_1 \triangle hp_{m,t} + \phi_3 \triangle y_{i,t} + W_{i,t-1}\phi_4 + \gamma_t + v_{i,t} \tag{1.4}$$

where $\triangle hp_{m,t}$ denotes the house price growth from period $t-1$ to t in MSA m where household i lives. $v_{i,t}$ is the error term. The rest of variables are defined as in model (1.3). The second stage is

$$I(Extract)_{i,t} = \theta_0 + \theta_1 \widehat{\triangle hp_{i,t}} + \theta_2 \triangle y_{i,t} + W_{i,t-1}\theta_3 + \gamma_t + \varepsilon_{i,t}. \tag{1.5}$$

Table 1.11 shows the results. The first column in the left panel shows that MSA level house price growth is a strong predictor of the change in households' self-reported home value. The second column in the left panel shows a similar, but higher extraction response as in the baseline results in Table 1.10. The F-statistic in the first stage indicates that the instruments are strong, so the estimator is consistent and asymptotically normal. The right panel of Table 1.11 shows age-specific extraction responses to house price shocks, and the results are similar to Table 1.10.

The second set of instruments is the MSA level housing supply elasticities developed by Saiz (2010). These elasticities measure the amount of developable land in metropolitan

areas, which help to predict the change in local house prices when demand shocks hit local housing markets. The identification assumption is that housing supply side conditions are not affected by individual household equity extraction decisions. Since housing supply elasticities are time invariant, limiting the variation in the instruments to the cross-section only, I discuss detailed estimation strategies and results for this set of instruments in Appendix A.1. The instrumental variable estimates are quite similar to the OLS estimates, suggesting that house price endogeneity is not a concern. Either way, the house price shock increases the propensity of extracting home equity, with young homeowners most responsive.

1.3   Model

In this section, I study a dynamic stochastic partial equilibrium life-cycle model designed to be consistent with the stylized facts documented in Section 1.2. In this model, households consume two goods: housing and non-housing. There are three forms of asset: liquid savings (such as riskless savings account), mortgage loans, and houses as collateral for borrowing. Homeowners have to pay a fixed cost to adjust the mortgage debt above or below the predetermined level. In addition, households face liquidity constraints and an extremely large transaction cost to downsize their homes.

My analysis builds on Berger et al. (2015), who use a life-cycle model to study the sensitivity of aggregate consumption to house prices. There are three key differences. First, whereas Berger et al. (2015) describe a theoretical model of consumption, the current paper is concerned with the ability of this type of model to explain the empirical correlations between home equity extraction and housing investment expenditures documented in Section 1.2.2. I show that borrowing frictions and liquidity constraints are the key features that help to replicate and explain these empirical correlations. Second, whereas Berger et al. (2015) were only concerned with the consumption response to house price shocks, the current paper puts equal emphasis on consumption and residential investment, and considers a wider range of shocks, including but not limited to house price shocks. Third, I assess the ability of a model with all of these shocks combined to explain the historical evolution of the data during 2000 to 2013, and I quantify the importance of the home equity-based borrowing channel for transmitting these shocks.

1.3.1 Setup

The economy is populated with overlapping generations of households whose income and assets differ across the life cycle. The model frequency is annual. In each year a mass of households is born and lives for J periods. In the first J_y periods of life, households work and earn labor income. In the remaining $J - J_y$ periods, households retire and receive a fixed income each period. Households are endowed with an initial housing stock, a pre-existing mortgage balance and an initial amount of liquid assets. In each period of the life cycle, households make decisions on non-housing consumption expenditures (hence consumption), housing investment expenditures, liquid savings, and how much to change on their mortgage borrowing. Households leave their total wealth at the end of their life as a bequest.

A household born in time t maximizes expected lifetime utility,

$$E_t\left[\sum_{j=0}^{J-1}\beta^j u(c_{j,t+j},h_{j,t+j})+\beta^J\Phi(w_{J,t+J})\right]$$

where the first subscript of a variable denotes the household's age and the second subscript denotes time. c and h denote consumption and the housing stock, respectively. It is assumed that the flow service generated by the housing stock is proportional to the housing stock. The second term inside the expectation operator represents the discounted utility from leaving a bequest, specified by the bequest function Φ (see the functional form in Section 3.3). $w_{J,t+J}$ denotes the total wealth at the end of the household's life.

Events in any period of life occur in the following sequence: (1) income and the aggregate state are realized. (2) Liquid savings carried from the previous period earn returns. (3) Housing service provided by the predetermined housing stock is consumed. (4) The housing stock depreciates, and the collateral value is determined. (5) Homeowners decide whether to change their mortgage balance. If they do, they pay a fixed cost, choose a new mortgage balance not exceeding the collateral value, and agree on a new repayment plan. If they do not, they make a repayment according to the original mortgage terms, and the balance evolves according to that plan. (6) Housing investment, consumption and liquid savings are chosen.

I consider a fully amortized mortgage scheme where the loan is amortized over the remaining life of the borrower.[18] The periodic repayment can be calculated based on a

---

[18]As in Wong (2015), this assumption is made to reduce the dimension of the state space. An alternative amortization structure would be a constant term schedule, such as amortizing over 15 or 30 years, which introduces an additional state variable, i.e., the remaining terms of the mortgage loan.

repayment formula, derived by assuming a constant payment in each period and a full repayment at the end of the term.[19] Given the principal amount b, mortgage rate r, and contract term T, the per-period repayment calculated using the formula is $M(b,r,T) = \frac{rb}{1-(1+r)^{-T}}$. When the mortgage rate is constant, each periodic payment is the same. When the mortgage rate is changing, I allow an automatic adjustment of the periodic repayment according to the prevailing mortgage rate, so borrowers pay adjustment costs only when they change their mortgage balances.[20]

The mortgage balance evolves as a borrower makes a repayment. Specifically, if a borrower of age j at period t with an initial balance $b_{j,t}$ chooses not to change the mortgage balance, she pays $M(b_{j,t}, r_t, J - j + 1)$, and the mortgage balance at the beginning of $t+1$ is $(1 + r_t)b_{j,t} - M(b_{j,t}, r_t, J - j + 1)$.

1.3.2 The Household Problem

At time t, the aggregate state is characterized by the house price p_t, the cost of improving or building homes p_t^I, and the mortgage rate r_t^b. Let S_t denote the aggregate state, where $S_t \equiv (p_t, p_t^I, r_t^b)$. A household of age j at time t, given her housing stock $h_{j,t}$, mortgage balance $b_{j,t}$, liquid savings $a_{j,t}$, income $y_{j,t}$, and the aggregate state S_t, chooses whether to change the current mortgage balance by comparing the value of changing, $V_{j,t}^C$, and not changing, $V_{j,t}^N$. I suppress the time subscript t for describing the household's problem. The higher value between the two options is

$$V_j(h, b, a, y; S) = \max\left\{V_j^C(h, b, a, y; S), V_j^N(h, b, a, y; S)\right\}.$$

If the household chooses to change her mortgage balance, the value function is given by

$$V_j^C(h, b, a, y; S) = \max_{h', b', a', c} u(c, h) + \beta E_j\left[V_{j+1}(h', b', a', y'; S')\right]$$

$$\text{s.t.} \quad c + a' + p^I\left[h' - h(1 - \delta)\right] = y + (1 + r^a)a - (1 + r^b)b + b' - F$$

$$b' \le \frac{(1 - \theta)(1 - \delta)}{1 + r^b}ph \tag{1.6}$$

$$h' \ge (1 - \delta)h$$

$$a' \ge 0; \quad b' \ge 0$$

---

[19] This formula is also called the mortgage calculator and is adopted by most mortgage providers.

[20] This mortgage scheme is similar to an adjustable rate mortgage structure. I discuss the implications of the model when adopting a fixed rate structure in Section 1.6.3.

where F denotes the loan adjustment cost, θ denotes the down payment rate, δ denotes the housing stock depreciation rate, and r^a is the return on liquid savings.

The first line in the constraint set is the budget constraint, where $p^I\left[h' - h(1-\delta)\right]$ is the housing investment expenditures at unit cost p^I. The second line is the collateral constraint that requires the new mortgage balance to be below the housing collateral value, which is jointly determined by the house value ph, the down payment rate θ, the depreciation rate δ and the mortgage rate r^b. The third line is the irreversible investment constraint that prevents households from downsizing their housing stock. An alternative interpretation of this constraint is an extremely large transaction cost on downsizing homes. The rationale for including such a constraint is to capture the life-cycle housing consumption profile documented by Yang (2009). Using data from the Survey of Consumer Finances (SCF), Yang shows that the housing consumption profile increases monotonically over the life-cycle, before flattening out. She proposes that the main theoretical explanation for the flat portion in later life is large transaction costs on downsizing the home.[21] The last line in the constraint set requires both liquid savings and the mortgage balance to be non-negative.

If the household chooses not to change her mortgage borrowing, the value function is given by

$$
\begin{aligned}
V_j^N(h,b,a,y;S) = \max_{h',a',c} \quad & u(c,h) + \beta E_j\left[V_{j+1}(h',b',a',y';S')\right] \\
s.t. \quad c + a' + p^I\left[h' - h(1-\delta)\right] &= y + (1+r^a)a - (1+r^b)b + b' \\
b' &= (1+r^b)b - M \\
h' &\geq (1-\delta)h \\
a' &\geq 0;
\end{aligned}
\tag{1.7}
$$

where $M \equiv M(b, r^b, J - j + 1)$ is the periodic mortgage payment calculated from the repayment formula. When the household chooses not to change mortgage borrowing, the next period mortgage balance b' is not a choice variable, but is determined by the second line in the constraint set of Problem (1.7).

Households face income uncertainty during their working life. Following Berger et al. (2015), the logarithm of the income process is specified as

$$
\log(y_{j,t}) = \chi_j + z_{j,t},
\tag{1.8}
$$

---

[21]Without this constraint, households in my model would downsize the housing stock to repay their mortgage before retirement and to finance their consumption in retirement years, which implies a sharply declining housing stock toward the end of the life cycle, inconsistent with the data.

where χ_j is an age-specific deterministic component. $z_{j,t}$ is the idiosyncratic shock to income, which evolves according to

$$z_{j,t} = (1 - \rho_z)\bar{z} + \rho_z z_{j-1,t-1} + \varepsilon^z_{j,t}, \quad \varepsilon^z_{j,t} \sim^{i.i.d.} (0, \sigma^2_{ez}), \tag{1.9}$$

where $\bar{z}$ is the unconditional mean of $z_{j,t}$, ρ_z is the persistence parameter, and $\varepsilon^z_{j,t}$ is a mean zero i.i.d. shock with variance σ^2_{ez}. Households have rational expectations toward the change in their income. Given $z_{j,t}$, $z_{j+1,t+1}$ is normally distributed with a conditional mean of $(1 - \rho_z)\bar{z} + \rho_z z_{j,t}$ and a conditional variance of σ^2_{ez}.

1.3.3 Solution Methods

The model is solved numerically by backward induction using a two-step procedure. In the first step, I discretize the state space and then solve the value functions over fixed grids of the states. In the second step, I obtain the policy functions by solving the optimization problem over denser grids, given the value functions obtained in the first step. The numerical procedure is described in detail in Appendix A.2.

1.4 Calibration

In order to assess the quantitative implications of this model, the model parameters are calibrated. A summary of the parameter values can be found in Table 1.12.

Age is indexed by $j = 0, ..., J - 1$. Households enter the life cycle at age 26, work for 35 years, retire at age 60 and live another 20 years in retirement, so $J = 55$ and $Jy = 35$. The initial housing stock, the initial mortgage balance, and the initial total wealth are set to match the mean of their counterpart in the PSID for age 20-25 households.

The utility function is of Cobb-Douglas form,

$$u(c_{j,t}, h_{j,t}) = \frac{1}{1 - \sigma} \left(c^\alpha_{j,t} h^{1-\alpha}_{j,t} \right)^{1-\sigma}$$

where σ denotes the inverse of the inter-temporal elasticity of substitution, and α denotes the expenditure share of consumption. Following standard consumption literature, I set $\sigma = 2$. I set $\alpha = 0.81$ to match the distribution of the ratio of housing investment expenditures over income across age bins in the PSID data. I set the discount factor $\beta = 0.935$ to match the distribution of the wealth to income ratio across age bins in the PSID data (see Section 1.5.1).

Households leave their total wealth at the end of their life as a bequest. The bequest function is specified as

$$\Phi(w) = \eta \frac{w^{1-\sigma}}{1-\sigma}$$

where $w \equiv (1+r^a)a - (1+r^b)b + p^I h(1-\delta)$ denotes total wealth. η is the bequest parameter. I set $\eta = 6$. This parameter affects borrowing and investment decisions in the last few years of the life cycle. For small η, the model generates a spike in the extraction rate toward the end of the life cycle. This is because, as impatient households deplete all their liquid savings, they finance retirement consumption by extracting home equity. Since there is no such spike in the data, I choose a large η such that the extraction rate remains roughly constant during retirement.

I use the PSID data to estimate both the deterministic and the idiosyncratic component of the income process specified in Equations (1.8) and (1.9). To obtain the deterministic component, χ_j, I regress the log of deflated annual household income on the first and second order polynomial of the household head's age. I then normalize the fitted age profile by subtracting the fitted value of the age 26 households, so that the permanent income at age 26 is 1.

To estimate the distribution of the stochastic component, $z_{j,t}$, I calibrate ρ_z and σ_{ez} by taking the residual from the χ_j regression described above and estimating an AR(1) process.[22] The estimates are $\rho_z = 0.9$ and $\sigma_{ez} = 0.18$. I assume that the average income path of a cohort over its life cycle is equal to the permanent age profile, i.e., $E_{j,t}y_{j,t} = \exp(\chi_j)$, which implies $E[\exp(z_{j,t})] = 1$. Therefore $\bar{z} = -\frac{\sigma_z^2}{2}$, assuming $z_{j,t}$ is normally distributed.

I impose a fixed annual income structure during retirement. Every year, retirees receive a constant amount that is a ζ fraction of the permanent income in the last working age. In the PSID data, the annual income of households aged 65 and above is about 60% of households aged 56 to 60, so I set $\zeta = 0.6$.

The housing depreciation rate is set at $\delta = 0.0227$, following the depreciation rate of residential 1-to-4 unit structures, as published by the Bureau of Economic Analysis (BEA). Following Berger et al. (2015), the down payment rate, θ, is set to 25%. The fixed cost of the mortgage adjustment is set at $F = 0.025$. This number is derived from the information in *A Consumer's Guide to Mortgage Refinancings*, published by the Federal Reserve Board in 2008, which shows that the closing costs of refinancing a mortgage are about 2-6 percent of the outstanding principal. Using the average outstanding principal and income reported

---

[22]Since the PSID is a biennial survey, the annual income is reported for every other year, so I cannot estimate Equation (1.9) directly. By iterating Equation (1.9) by one period, $z_{j,t} = (1+\rho_z)(1-\rho_z) + \rho_z^2 z_{j-2,t-2} + (\varepsilon_{j,t}^z + \rho_z \varepsilon_{j-1,t-1}^z)$. This allows me to estimate the AR(1) process using $z_{j,t}$ and $z_{j-2,t-2}$, and to recover the original parameters, ρ_z and σ_{ez}.

in the PSID, I infer that fixed costs represent between 2.5 and 7.7 percent of households' income. I choose the lower end of this range for my calibration.

The steady state house price, p, and the cost of improving and building homes, p^I, are normalized to 1. The steady state mortgage rate r^b is set equal to 0.04, based on the historical average of the 30-year fixed mortgage rate net of inflation during 1990-2015. The liquid asset return, r^a, is set to 0.01.

1.5   Steady State Analysis

This section characterizes the optimal life-cycle choices in steady state by simulating the life-cycle profiles of 4,000 households born at age 26.[23]   First, I show that the average life-cycle profiles simulated by this quantitative model match the life-cycle profile of several key variables in the survey data. Second, I show that at the household level, the model simulated data capture the empirical correlations between home equity extraction and housing investment expenditures as documented in Section 1.2.2. The model helps interpret these correlations.

1.5.1   Average Life-cycle Profile

Figure 1.2 shows the average life-cycle profiles simulated by the model in steady state. The average housing stock peaks at age 60, and then gradually declines because of depreciation. Income, calibrated using the PSID data, follows a hump shape during the working ages between 26 to 60, and then stays constant during retirement. Consumption follows a hump shape. Before age 48, it increases because of liquidity constraints, and after age 48, it decreases due to impatience. Before retirement, income is systematically above consumption, whereas after retirement, it is below, until the last few years of the household's life. Households accumulate liquid savings before retirement for two reasons: precautionary saving motive due to income uncertainty, and financing retirement consumption.   After retirement, liquid savings are quickly depleted, again due to impatience. Mortgage balances peak around age 35 and steadily decline over the life cycle. A small spike appears in mortgage balances close to the end of the life cycle when households deplete liquid savings and extract equity to finance consumption. Since extractions incur fixed costs, old households keep unused equity in liquid savings, which explains the little spike in liquid savings close to the end of the life cycle.

---

[23]I assume that households are endowed with the same initial assets and housing stock. Allowing for heterogeneity in the initial asset holdings or housing stock does not change the aggregate outcomes obtained by averaging across all households.

Figure 1.3 compares the life-cycle profile on total wealth, liquid savings, housing investment expenditures and consumption simulated by the model with the survey data. The graphs are plotted over working ages, because my model does not incorporate uncertainty during retirement, such as health shocks or income uncertainty, that could result in an accumulation rather than depletion of liquid savings during retirement. Therefore, I focus on outcomes over the working life.

The model profiles are averaged over 5-year age bins to be compared with the data. I normalize total wealth, liquid savings and housing investment expenditures by dividing the average income of the first age bin, so the units on the vertical axes are in proportion to the initial income. I normalize consumption of all age bins by dividing consumption of the first age bin.

I construct empirical life-cycle profiles based on the PSID data and the Consumer Expenditure Survey (CE) data along the same lines. The total wealth and liquid savings are taken from the PSID, deflated by the CPI, then averaged across households from all years by age bins, and finally normalized by the average income of the age 26-30 households.[24] The investment expenditures include home improvement, repair and maintenance, property tax, and homeowner insurance, but not mortgage payment. For first-time home buyers in the PSID, I add their down payment to their housing investment expenditures.[25] For consumption, I average, across each age bins, the non-housing expenditures from the PSID 2005-2013 data and from the CE 1994-2014 data, respectively, following the same sample selection criteria as in Section 1.2.1, and I normalize the non-housing expenditures by those of youngest households.

The calibrated model successfully captures the patterns in the survey data. Total wealth and liquid savings are increasing over the working life. Investment expenditures on housing are declining with age, and consumption is hump-shaped. The latter pattern has also been empirically documented in Fernandez-Villaverde and Krueger (2006) and Yang (2009). Consumption in the model has more curvature than in the data, probably due to the mismeasurement of consumer expenditures.[26] The magnitude of investment expenditures in the model is mainly affected by two parameters: the non-housing expenditure share α,

---

[24]In the PSID, total wealth is the sum of liquid and illiquid assets. Liquid assets include safe liquid assets (checking and savings accounts, money market funds, certificates of deposit, government savings bonds, and treasury bills) and risky assets (stock shares), net of other non-mortgage debt (credit card charges, student loans, medical or legal bills, and loans from relatives). Illiquid assets include home equity, value from real estate, IRA and private annuities, other assets and the value of farms or businesses.

[25]I identify first-time home buyers in the data as those who report taking a non-refinanced mortgage and below age 35.

[26]Changing the parameter ρ_z, which governs the persistence of the idiosyncratic income process, to a smaller value reduces the consumption curvature, but then less wealth is accumulated than in the survey data. Since wealth is more precisely measured than consumption, I use the calibrated value of ρ_z as in Section 1.4.

and the fixed cost F. Given that the value of F can be pined down by extraneous evidence, the parameter α in Section 1.4 was chosen to minimize the average distance between the model and the survey data for housing investment expenditures in Figure 1.3.

1.5.2 Household Level Profile

The life-cycle profiles of individual households show that homeowners extract home equity occasionally, especially when they are young, consistent with the initial rising portion of the average mortgage balance path. When households, especially the young, tap their equity, they spend a substantial fraction of their equity on housing investment expenditures. To show that the model is able to match and explain much of the empirical correlations documented in Section 1.2.2, I run the same regression models using the data simulated by the model. I exclude retired households because old homeowners have already accumulated enough housing stock and do not make further investment in housing.

The extensive margin correlation, as empirically estimated in Equation (1.1), using the model simulated data, is estimated by

$$I(Improvement)_{i,j} = \alpha_0 + \alpha_1 I(Extract)_{i,j} + \varepsilon_{i,j} \tag{1.10}$$

where $I(Improvement)_{i,j}$ is an indicator of whether household i of age j spends more than 5 percent of annual income on housing investment.[27] $I(Extract)_{i,j}$ is an indicator of whether household i of age j extracts home equity. I also run this specification for different age groups. Results in Table 1.13 show that home equity extraction is correlated with substantial housing investment expenditures. The equity extractors are 13 percent more likely to invest substantially on housing investment than non-extractors. This correlation is largest among young households. Although these correlations are higher in the model than in the data, they qualitatively match the results in Table 1.4 and 1.5. Later in life, the propensity of making substantial housing investment between the two groups is reversed. One reason is that the housing stock is already large in mid-life, so the value of extra housing service diminishes. Another reason is that the old extractors extract home equity primarily to smooth consumption.

On the intensive margin, I estimate the correlation between equity extraction and housing investment expenditure growth, using the specification similar to Equation (1.2),

$$\frac{\triangle Inv_{i,j}}{Total\ spending_{i,j-1}} = \beta_0 + \beta_1 I(Extract)_{i,j} + \varepsilon_{i,j} \tag{1.11}$$

---

[27]I experimented with different thresholds, such as 10, 15 and 20 percent. The results are quite similar.

where the dependent variable denotes the change in housing investment expenditures of household i of age j as a fraction of her previous year total spending. $I(Extract)_{i,j}$ is an indicator of whether this household extracts home equity at age j. Results in Table 1.14 show that the housing investment expenditure growth of home equity extractors is 9 percentage points higher than non-extractors. Young extractors have larger housing investment expenditure growth than similarly aged households. These estimates closely track those in Table 1.6 and 1.7 based on the survey data.[28]

Not only does the model generate correlations similar to the survey data, but it helps to understand these correlations. By simulating the life-cycle profiles of individual households, it can be shown that young households, starting their life with small houses, want to make further investment in housing. Liquidity constraints imply that households are short of cash when they do not extract equity. Borrowing frictions imply that households extract equity only occasionally, and when they do, they remove a chunk of cash and invest it in housing. The key structural assumptions that generate the positive correlation between equity extraction and housing investment expenditures are (a) the fact that housing serves both as a consumption good and as a collateral asset, (b) the existence of liquidity constraints, and (c) the presence of borrowing frictions.

1.6 Shocks in the Housing Market

In this section, I use the calibrated model to study the impact of three distinct housing market shocks: an unexpected permanent increase in real house prices, an unexpected permanent increase in the real cost of home improvement and building, and an unexpected permanent reduction in the real mortgage rate. I focus on permanent shocks because real house price indexes and mortgage rates are highly persistent in time series data.[29] For each shock, I analyze both the impact responses for different age groups and the aggregate responses over a multi-year horizon. I show that the response of housing investment is much larger than that of consumption, and that the housing investment responses are mainly driven by home equity extractors.

---

[28]Using model simulated data, I also estimate the regression specifications that include the same control variables as in Section 1.2.2. The results are similar to those in Tables 1.13 and 1.14.

[29]For real house prices, I fit an AR(1) process to the quarterly house price index from 1975q1 to 2015q3 deflated by the CPI. The estimated coefficient was 0.993 (s.e.=0.01), indicating near perfect persistence. For the real cost of improvement, I fit an AR(1) process to the annual construction material price index from 1947 to 2015. The AR(1) coefficient was 0.98 (s.e.=0.03). For the real mortgage rate, I fit an AR(1) process to the quarterly 30-year fixed mortgage rate from 1971q1-2015q3 adjusted for CPI inflation. The estimated AR(1) coefficient was 0.976 (s.e.=0.02), again close to a random walk.

1.6.1 House Price Shocks

Most of the existing literature has considered the experiment of simultaneously shocking the real house price (or, equivalent, the value of housing collateral) and the cost of improving, building and purchasing homes. In contrast, I compute responses to each of these shocks, one at time, starting with the real house price, without assuming that shocks to the real house price are necessarily passed one for one to the cost of improving, building and purchasing homes.

Figure 1.4 shows the impact responses of the extraction rate, and of consumption and housing investment expenditures to a 1 percent unexpected permanent increase in the real house price by age group. In the model, a higher house price increases the collateral value, relaxes the collateral constraint, and stimulates borrowing through equity extraction. The left panel shows that a 1 percent increase in the house price causes a 0.7 percent increase in the equity extraction rate on average across all age groups, and this response is largest among young homeowners, consistent with the regression evidence in Section 1.2.3. Both consumption and housing investment expenditures increase. The housing investment expenditures respond much more than consumption, especially for young households.

Figure 1.5 decomposes the responses of consumption and housing investment expenditures between equity extractors and non-extractors.[30] It shows that almost all the effect of house prices are driven by home equity extractors, especially young extractors. Figure 1.6 focuses on the aggregate responses of the economy for a horizon of up to five years. The equity extraction rate increases on impact, before gradually declining. In the limit, it reaches a new, higher steady state level. The responses of consumption and housing investment follow a qualitatively similar pattern.

1.6.2 Improvement and Building Cost Shocks

Next, consider the responses to a 1 percent unexpected permanent increase in the real cost of home improvement, building and purchases, p^I. This shock creates an income effect, a substitution effect, and a wealth effect. The first two effects are due to the relative price change between the housing and the consumption good. The third effect arises from the proceeds of the net sale of households' housing stock. The income effect is negative for both housing investment and consumption, because housing services in the model are assumed to be a normal good. The substitution effect is positive for consumption and negative for housing investment, because there are only two goods in the model. Since I do not allow households to downsize their homes, the wealth effect is non-positive. Therefore,

---

[30]The units are shown in levels, so the changes in two groups are added up to the total change.

theory predicts that housing investment expenditures should fall in response to the cost shock. The response of consumption depends on how strong the substitution effect is.

Figure 1.7 shows that an unexpected permanent increase in the improvement, building and purchasing cost does not change much the extraction rate on average, but induces a heterogeneous response across households. The young, originally planing to extract equity and to invest in housing, now delay extraction due to the higher investment cost. Some old households, originally not planning to tap their home equity, now, due to the higher investment cost, extract equity to finance spending. Consumption in Figure 1.7 increases due to the substitution effect, whereas the housing investment falls, as predicted by the theory.

Figure 1.8 decomposes the responses of consumption and housing investment expenditures between equity extractors and non-extractors. In the housing investment panel, the impact response for both extractors and non-extractors are negative, and non-extractors cut more on housing investment expenditures. The overall decline in housing investment is expected, given the higher cost of investment. Young households are disproportionately affected by this cost shock, because they were, on average, investing more in housing before the shock. In the consumption panel, the impact responses for both extractors and non-extractors are positive for all age groups but especially so for young non-extractors. The increase in consumption across all age groups reflects the substitution effects. The disproportionate increase among young non-extractors reflects a higher expenditure share on housing investment before the shock. Figure 1.9 shows the corresponding aggregate responses. The extraction rate changes little on impact and peaks after one year before declining, because many households delay their extraction for one year. Consumption increases on impact before declining very slowly. It converges to a permanently higher level in the long run. Housing investment drops sharply on impact before gradually recovering to a value below the original steady state.

1.6.3 Mortgage Rate Shocks

Recent empirical and theoretical work has stressed the importance of the mortgage market in transmitting monetary policy shocks to household consumption (see, e.g., Aladangady (2014), Bhutta and Keys (2016) and Wong (2015)). Recall that in the model described in Section 3.2, the change in the mortgage rate applies to all borrowers, regardless of whether they change their mortgage balance. Households pay a fixed cost only when they change their mortgage balance. This assumption, resembling the key feature of adjustable rate mortgages in the U.S. market, helps to distinguish two incentives in extracting home equity,

as discussed in Hurst and Stafford (2004). One is the financial option incentive from paying less interest on the same loan amount. The other is the consumption smoothing motive from obtaining cash at a lower cost. In the model, a lower mortgage rate stimulates equity extractions that are driven by the consumption smoothing purpose. Alternatively, one could consider a model with a fixed rate mortgage structure in which a borrower pays fixed costs to change both the amount of borrowing and the rate, as in Wong (2015). In that case, the response of the extraction rate will be further amplified, because adjusting the mortgage becomes more attractive.[31]

Figure 1.10 shows the impact responses of the equity extraction rate, and of consumption and housing investment expenditures to a 1 percent unexpected permanent reduction in the real mortgage rate by age group. The extraction rate rises for all age groups and peaks at the young-to-middle-aged group. Consumption and housing investment expenditures follow the same pattern as the equity extraction rate. These responses are not monotonically declining with age. This is because a lower mortgage rate, unlike a higher house price, does not increase the available equity immediately, so paying a fixed cost to extract equity is most attractive to those who are liquidity constrained and have substantial home equity accumulated in their houses, i.e., young-to-middle-aged households. The fact that young households aged 26 to 30 have a lower exaction rate than the middle-aged households has two reasons. First, these households are collateral constrained and hence do not benefit as much from a lower mortgage rate. Second, a lower mortgage rate automatically reduces the interest payments on existing balances, further lowering young households' incentive to extract equity.

Figure 1.11 decomposes the responses of consumption and housing investment expenditures between equity extractors and non-extractors. The consumption panel shows that young extractors drive the consumption response among young households, whereas non-extractors contribute to the consumption increase among middle-aged and old households. Similar pattern is observed in the housing investment panel. Non-extractors increase both consumption and housing investment expenditures because a lower mortgage rate reduces interest payment, hence creating a positive wealth effect. Figure 1.12 shows the corresponding aggregate responses. All three variables increase on impact, and then gradually converge to a new, higher steady state.

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[31]The analysis of the mortgage rate shock in this paper differs from Wong (2015) in that Wong studies a set of shocks including income, house prices, and mortgage rates that are induced by a monetary policy shock, whereas my analysis focuses on the mortgage rate shock in isolation.

1.7 Consumption and Residential Investment Cycles

In this section, I feed U.S. data for real house prices, cost indexes of home improvement and building, and real mortgage rates into the calibrated model of Section 3.2. The objective is to evaluate the model's ability to explain the evolution of consumption and residential investment between 2000 and 2013. This exercise is designed to shed light on the extent to which home equity based-borrowing contributed to the boom-bust cycle in the United State during this period.

The upper panel of Figure 1.13 shows the three U.S. time series fed into the model. The real house price series, p_t, is the historical house price index published by the Federal Housing Finance Agency, deflated by the CPI. The real cost of home improvement and building, p_t^I, is proxied by the producer price index of construction materials obtained from the Bureau of Labor Statistics, deflated by the CPI. The 30-year fixed mortgage rate adjusted for inflation is used as the real mortgage rate, r_t^b.

As in Berger et al. (2015), in each period t, households take the path of the future house price as deterministically given. In the baseline specification, future house prices are assumed to be equal to the current house price. Analogous assumptions are made with respect to the mortgage rate and the cost of building and improving homes.

The lower panel of Figure 1.13 shows the evolution of consumption, residential investment and the home equity extraction rate simulated by the calibrated model, conditional on the U.S. data. The model generates a boom-bust cycle for both consumption and residential investment. This evidence sheds light on what happened during the boom and the following contraction period. During the boom, as house prices increased and mortgage rates declined, the aggregate housing stock accumulated quickly due to the investments made by home equity extractors, especially young extractors. The growing housing stock facilitated more home equity-based borrowing that in turn financed spending on both housing and non-housing expenditures. In the subsequent bust period, when house prices fell sharply, fewer households extracted equity, housing investment declined, and the collateral value shrank, further dampening equity extraction and aggregate spending.

In Figure 1.14, I evaluate the model's ability to explain the U.S. data by comparing the model generated data to the corresponding U.S. data. Since my model abstracts from trend growth in income, Figure 1.14 shows the detrended NIPA data for real personal consumption expenditures and residential investment during 2000-2013. Although the model is not intended to explain the entire business cycle, it replicates several key features of the U.S. data, especially for residential investment, suggesting that the model is able to capture an important aspect of the U.S. economy. For consumption, the fit is less tight, but

the model still captures the overall trend in consumption, especially for the boom period between 2000 and 2005.

The model provides an answer to the question of whether home equity extractors were responsible for these cycles during the 2000s. We already know from the micro evidence that home equity extractors spent only a small fraction of the extracted funds on non-housing expenditures, breaking a direct link between equity extraction and consumption. There is, however, a more subtle link. The model shows that, although individual extractors spent only a small fraction of extracted equity on consumption, the share of the extractors among the population increased dramatically in the early 2000s. Figure 1.15 shows that the consumption share of home equity extractors rose from 3 percent in 2000 to 40 percent by 2005. As a result, the consumption by these extractors collectively was enough to create the consumption cycle shown in Figure 1.14.

Figure 1.15 also shows that the housing expenditures of home equity extractors disproportionately contributed to the evolution of residential investment during the boom period. For example, in 2005 when the house price peaked and the mortgage rate fell to a historical low, the residential investment share of home equity extractors increased from 7 percent to almost 80 percent, and almost all of the housing investment expenditures were made by young home equity extractors aged 26 to 45. Based on this evidence, I conclude that home equity extractors were directly responsible for the boom-bust cycle of residential investment during the 2000s.

An interesting question is why the model matches the aggregate data better during the boom period than during the bust period. For example, Figure 1.14 shows a negative spike in 2009 in the simulated data that is not found in the U.S. data. This discrepancy can be explained by the fact that in the model households are assumed to have adjustable rate mortgages, consistent with evidence in Chen and Stafford (2016) that adjustable rate mortgages are popular during periods of low interest rates. In 2009, an exceptionally high real mortgage rate implies in the model a large reduction in borrowers' disposal income, and therefore discouraged consumption through adjustable mortgage payments. However, in the real world by 2009, many households had switched to fixed-rate mortgages, protecting them from mortgage rate increases.

Whereas the U.S. has a well-developed home equity-based borrowing market, other countries, such as most Asian countries do not, raising the question of how quantitatively important this borrowing channel is in transmitting shocks in the housing market to consumption and residential investment. Allowing for home equity-based borrowing clearly enhances welfare relative to an economy with fully restricted borrowing markets. It is nevertheless useful to quantify the difference this channel makes for the aggregate data.

To quantify the extent to which aggregate shocks in the U.S. housing market were amplified by the home equity-based borrowing channel, in Figure 1.16, I compare the evolution of consumption and residential investment generated by the model with those from a standard two-goods incomplete markets model, in which collateral borrowing is impossible. Under this counterfactual, the fluctuations of consumption and residential investment solely arise from the change in the cost of improving and building homes.

For each of the variables of interest, I compute two summary statistics measuring the importance of the home equity-based borrowing channel. The first measure is the difference in the average deviation from the steady state across the two models. The second measure is the ratio of the standard deviations of the growth rates in the two models. Table 1.15 shows that the model raises the mean level of consumption by 1.3 percentage points (from 0.2 percent to 1.5 percent). This improvement, however, comes at the cost of a substantial increase in the variability of consumption growth. Similarly, the home equity-based borrowing channel pushes up the mean of residential investment from -4.7 percent in the counterfactual model to 23 percent in my model. Again, this increase in the mean is associated with much higher volatility.

1.8   Conclusion

A common view in the macroeconomic literature is that an increase in house prices stimulates consumption because homeowners take advantage of a higher collateral value of their homes to finance consumption. This view is inconsistent with empirical evidence that homeowners spend a substantial share of the extracted funds on home improvement and building rather than on consumer goods and services. That evidence is robust across time, across different data sources and even across countries. However, thus far, no economic explanation of this pattern in the data has been provided. Nor do existing studies explain the additional fact documented in this paper that this correlation is particularly high among young homeowners.

I use a structural model to provide a theoretically coherent and unified account of the relationship between home equity-based borrowing and the boom-bust cycle in consumption and residential investment that is consistent with the micro evidence. The key feature of the model that helps explain the data is the existence of borrowing frictions. The borrowing frictions in my model weaken the consumption response to shocks in the housing market compared to more conventional models. These frictions also generate lumpy investment in housing. The model implies that positive shocks in the housing market strongly stimulate housing investment expenditures through the home equity extraction

channel.

The boom-bust cycles in consumption and residential investment implied by this model are shown to match several key features of the corresponding U.S. cycles between 2000 to 2013. Although the model is not intended to provide a full description of the business cycle, it captures many of the key characteristics of the U.S. data. The model shows that the determinants of this cycle are different from the conventional wisdom that the consumption boom-bust cycle was caused by homeowners using home equity to finance consumption. The model highlights a more subtle mechanism linking the evolution of consumption to home equity-based borrowing. Although home equity extractors individually only spent a small fraction of their extracted funds on consumption, consistent with the micro evidence, the share of home equity extractors increased so much in the early 2000s that they collectively accounted for much of the consumption boom.

Table 1.1: Summary statistics of the PSID data

Year	# of Obs.	Mortgage balance($)	Home value($)	Equity extraction(%)	Cash-out Refi Freq.
99-01	1,216	72,690	149,771	27.8	33.1
01-03	1,280	86,551	178,508	36.6	61.1
03-05	1,293	98,915	223,222	34.0	52.2
05-07	1,314	112,192	254,017	31.1	46.7
07-09	1,425	122,784	227,707	25.3	31.9
09-11	1,523	131,887	215,705	21.1	34.9
11-13	1,555	134,290	219,422	17.4	30.1
Total	9,606	110,259	211,037	27.1	43.3

Notes: Mortgage balances and home values are shown in nominal terms, but are converted to 2009 dollars for the rest of the empirical analysis.

Table 1.2: Demographic characteristics of extractors and non-extractors

	Extractors	Non-extractors
Age	49.0	49.1
Male	0.83	0.83
White	0.67	0.70
Education (years)	13.4	13.7
Married	0.75	0.74
Family size	3.89	3.86
# Obs.	2,606	7,000

Notes: Samples are pooled from all years between 1999 and 2013.

Table 1.3: Financial conditions of extractors and non-extractors

Units: 2009 dollars	Extractors	Non-extractors
Previous Interview		
Income	92,702	93,688
Total Wealth	195,373	197,790
Liquid wealth	24,250	33,219
Home equity	110,972	95,341
Non-housing expenditures	26,747	26,259
Housing expenditures	23,481	22,308
Current Interview		
Income	91,892	94,999
Total Wealth	186,030	223,800
Liquid wealth	25,452	38,135
Home equity	94,382	109,652
Non-housing expenditures	27,533	26,365
Housing expenditures	25,166	20,101
Change in		
Income	-810	1,312
Total Wealth	-9,343	26,010
Liquid wealth	1,202	4,916
Home equity	-16,590	14,311
Non-housing expenditures	785	106
Housing expenditures	1,685	-2,206
# Obs.	2,606	7,000

Notes: Samples are pooled from all years between 1999 and 2013.

Table 1.4: Equity extraction and home improvement decision

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: $I(improvement)_{i,t}$				
$I(Extract)_{i,t}$	0.069	0.070	0.064	0.061	0.061
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
$\triangle y_{i,t}$ (%)		0.013	0.013	0.012	0.006
		(0.005)	(0.005)	(0.005)	(0.003)
$y_{i,t-1}$		0.074	0.075	0.074	0.020
		(0.009)	(0.009)	(0.009)	(0.015)
illiquid assets$_{i,t-1}$		0.006	0.006	0.007	0.002
		(0.003)	(0.003)	(0.003)	(0.003)
liquid assets$_{i,t-1}$		0.004	0.003	0.003	0.001
		(0.004)	(0.004)	(0.004)	(0.005)
$\triangle hp_{i,t}$ (%)				0.030	0.015
				(0.011)	(0.009)
Year Dummies	N	N	Y	Y	Y
Household FE	N	N	N	N	Y
# Obs.	9,606	9,606	9,606	9,606	9,606

Notes: y and $\triangle y$ denote the income level and the income growth rate, respectively. $\triangle hp$ denotes the growth rate of home value. Previous period income and wealth variables are in $100,000. Sample period:1999-2013. Estimation method: pooled OLS for column (1)-(4); fixed effect panel data model for column (5). Standard errors are clustered at household level. All regressions include household age, age squared, and change in family size.

Table 1.5: Equity extraction and home improvement decision, by age

	22-30	31-45	46-55	56-65	65+
	Dependent Variable: $I(improvement)_{i,t}$				
$I(Extract)_{i,t}$	0.176	0.062	0.049	0.065	0.042
	(0.047)	(0.013)	(0.013)	(0.019)	(0.024)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table 1.6: Equity extraction and expenditure growth

	Total	Nonhousing	Housing	Excl. mort.	Improv.
$I(Extract)_{i,t}$	0.096	0.015	0.081	0.046	0.044
	(0.018)	(0.008)	(0.016)	(0.008)	(0.008)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	9,606	9,606	9,606	9,606	9,606
Expenditure Share	1.00	0.55	0.45	0.21	0.07

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table 1.7: Equity extraction and housing expenditure growth, by age

	Housing expenditure growth of				
	22-30	31-45	46-55	56-65	65+
$I(Extract)_{i,t}$	0.167	0.084	0.089	0.078	-0.010
	(0.040)	(0.017)	(0.035)	(0.016)	(0.101)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table 1.8: Equity extraction and housing expenditure growth excl. mortgage, by age

	Expenditure growth of housing excl. mortgage				
	22-30	31-45	46-55	56-65	65+
$I(Extract)_{i,t}$	0.109	0.048	0.041	0.033	0.049
	(0.040)	(0.015)	(0.012)	(0.015)	(0.027)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table 1.9: Equity extraction and non-housing expenditure growth, by age

	Non-housing expenditure growth of				
	22-30	31-45	46-55	56-65	65+
$I(Extract)_{i,t}$	0.060	0.022	-0.006	0.024	0.046
	(0.038)	(0.013)	(0.013)	(0.017)	(0.037)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table 1.10: Equity extraction and house price shocks, OLS

	Dependent Variable: $I(Extract)_{i,t}$					
	All sample	22-30	31-45	46-55	56-65	65+
$\triangle hp_{i,t}$ (%)	0.128	0.200	0.171	0.128	0.091	0.119
	(0.018)	(0.084)	(0.038)	(0.030)	(0.018)	(0.061)
Controls	Y	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y	Y
# Obs.	9,606	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are described in model (1.3).

Table 1.11: Equity extraction and house price shocks, 2SLS

	1st stage	2nd stage	2nd stage: $I(Extract)_{i,t}$				
	$\triangle hp_{i,t}$	$I(Extract)_{i,t}$	22-30	31-45	46-55	56-65	65+
$\triangle hp_{m,t}$	0.88						
	(.058)						
$\widehat{\triangle hp_{i,t}}$		0.179	0.348	0.290	0.122	0.060	0.191
		(0.073)	(0.311)	(0.109)	(0.116)	(0.262)	(0.303)
F-stat	72.11						
# Obs.	5,951	5,951	213	2,095	2,041	1,196	406

Notes: Sample period:1999-2013. Estimation method: 2SLS. Standard errors are clustered at household level. Control variables are described in Equation (1.4) and (1.5).

Table 1.12: Calibration

Parameter		Value
Preference		
$u(c,h)$	Utility function	$\frac{(c^\alpha h^{1-\alpha})^{1-\sigma}}{1-\sigma}$
σ	Inverse of IES	2
β	Discount factor	0.935
α	Non-housing expenditure share	0.81
η	Utility weight on bequest	6
Income		
$\log(y)$	Log income process	$\chi + z$
χ	Deterministic age-specific income	
z	Idiosyncratic income shocks	AR(1)
ρ_z	Persistence of z	0.9
σ_{ez}	Standard deviation of z's error term	0.18
ζ	Retirement income as a fraction of the last working period's income	0.6
Housing and Mortgage		
δ	Housing depreciation rate	0.0227
θ	Down payment rate	0.25
F	Loan adjustment cost	0.025
Aggregate Variables		
p	Steady state house price	1
p^I	Steady state improvement cost	1
r^b	Steady state mortgage rate	0.04
r^a	Interest rate of liquid savings	0.01

Notes: This table shows calibrated parameters. See Section 3.3 for method description.

Table 1.13: Equity extraction and home improvement decision, simulated data

	Dependent Variable: $I(improvement)_{i,j}$				
	All sample	26-30	31-45	46-55	55-60
$I(Extract)_{i,j}$	0.134	0.354	0.151	-0.344	-0.305
	(0.005)	(0.010)	(0.008)	(0.014)	(0.016)
# Obs.	140,000	20,000	60,000	40,000	20,000

Notes: This table shows the results from estimating Equation (1.10) using model simulated data in the steady state. Estimation method: OLS.

Table 1.14: Equity extraction and housing expenditure growth, simulated data

	Dependent Variable: Housing spending growth of				
	All sample	26-30	31-45	46-55	55-60
$I(Extract)_{i,j}$	0.088	0.124	0.116	0.008	- 0.005
	(0.002)	(0.003)	(0.002)	(0.003)	(0.056)
# Obs.	136,000	20,000	60,000	40,000	16,000

Notes: This table shows the results from estimating Equation (1.11) using model simulated data in the steady state. Estimation method: OLS.

Table 1.15: Quantitative measures for the amplification effects

	Consumption	Residential Investment
Mean dev. from the steady state (%)		
Model	1.5	23.2
Counterfactual	0.2	-4.7
Difference	1.3	27.9
Standard dev. of annual growth rate		
Model	3.5	80.0
Counterfactual	0.2	7.5
Ratio	17.5	10.7

Notes: This table shows the quantitative measures to evaluate the role of home equity-based borrowing channel in transmitting shocks in the housing market between 2000 and 2013.
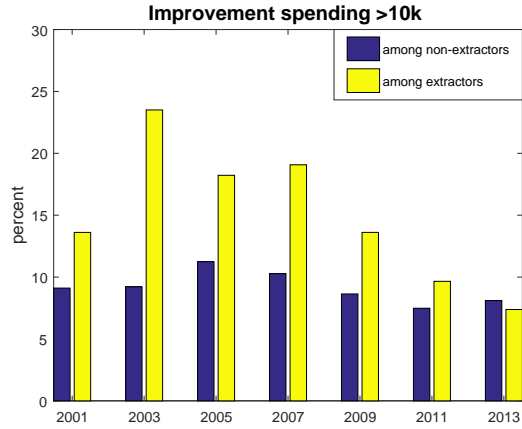
Figure 1.1: Home equity extraction and home improvement spending in PSID

Notes: Data source: PSID 1999-2013. This figure plots the fraction of homeowners making home improvement spending greater than $10,000.
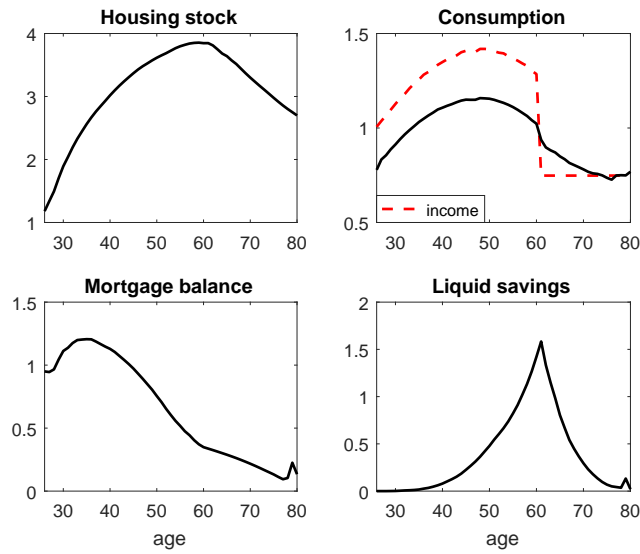
Figure 1.2: Average life-cycle profiles in steady state

Notes: This figure plots steady state life-cycle profiles by averaging across households of the same age. The units are in proportion to the income of households aged 26.
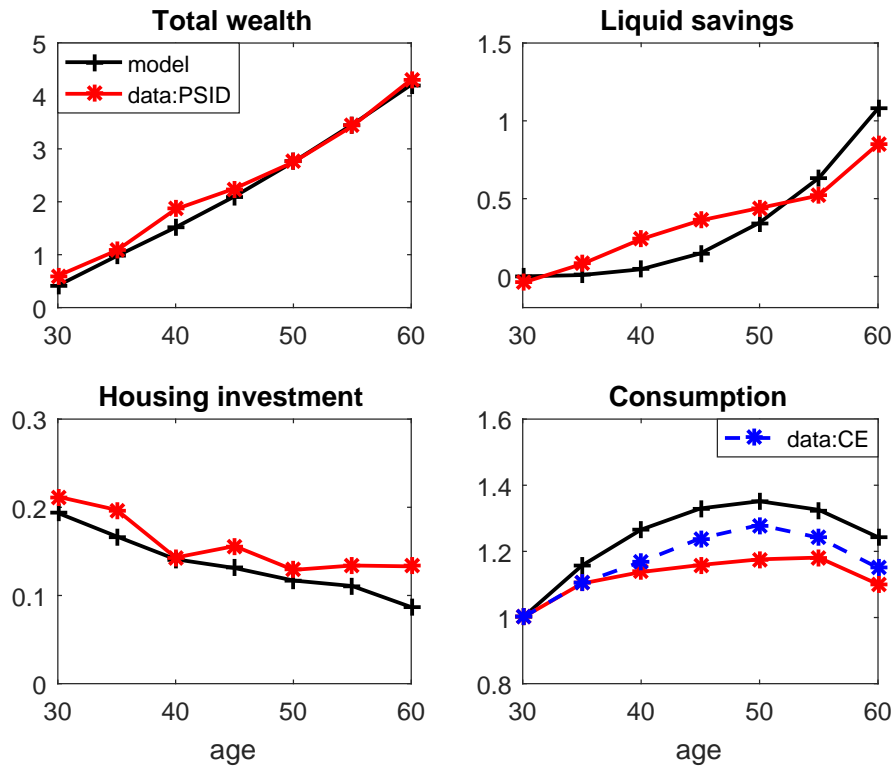
Figure 1.3: Model simulated data and survey data

Notes: This figure plots life-cycle profiles simulated by the model and constructed from survey data. Wealth, liquid savings and housing investment expenditures are in proportion to the income of households aged 26 to 30. Consumption is normalized by the consumption of households aged 26 to 30.
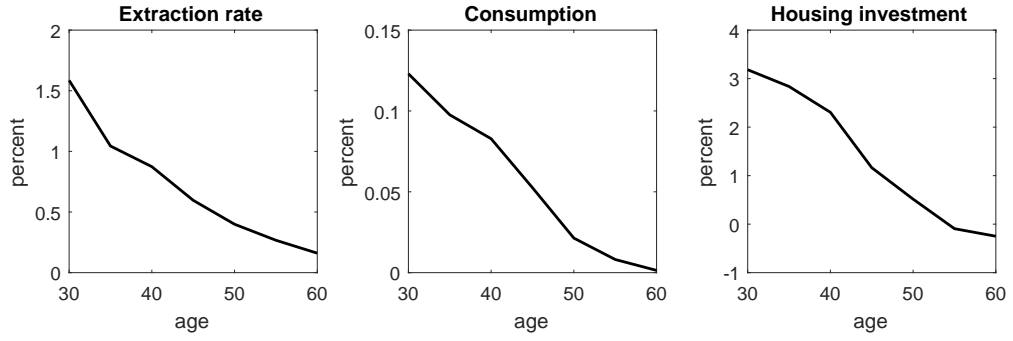
Figure 1.4: Impact responses to a permanent house price increase
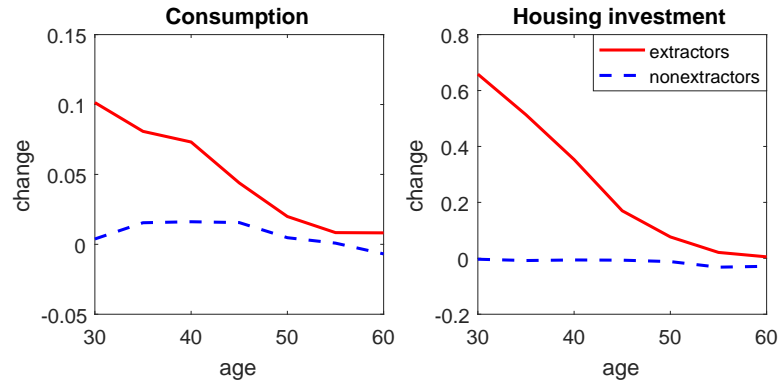
Figure 1.5: Impact responses to a permanent house price increase by extraction status
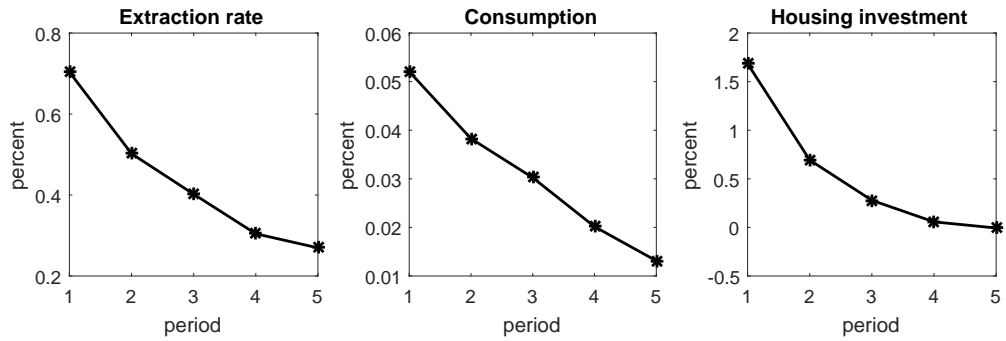
Figure 1.6: Impulse responses to a permanent house price increase
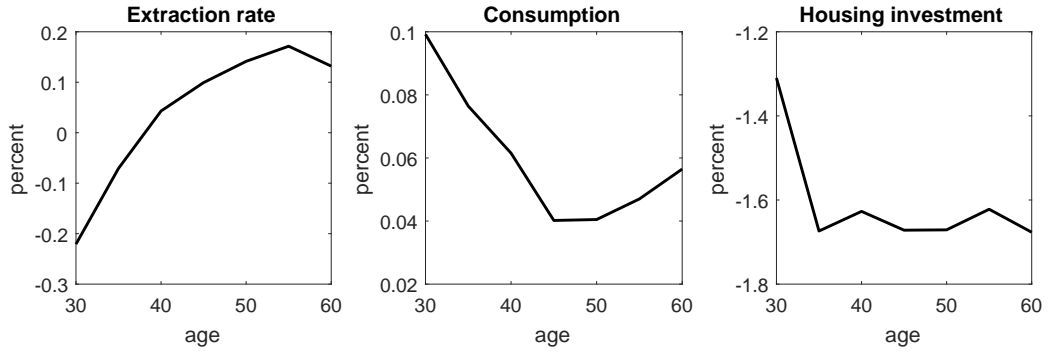
Figure 1.7: Impact responses to a permanent improvement cost increase
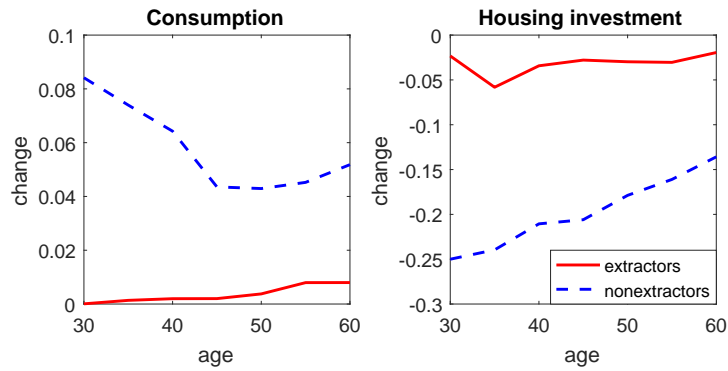
Figure 1.8: Impact responses to a permanent improvement cost increase by extraction status
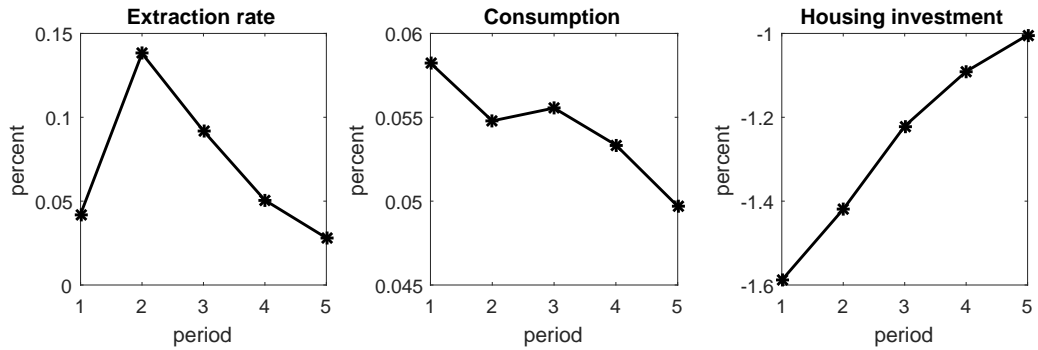
Figure 1.9: Impulse responses to a permanent improvement cost increase
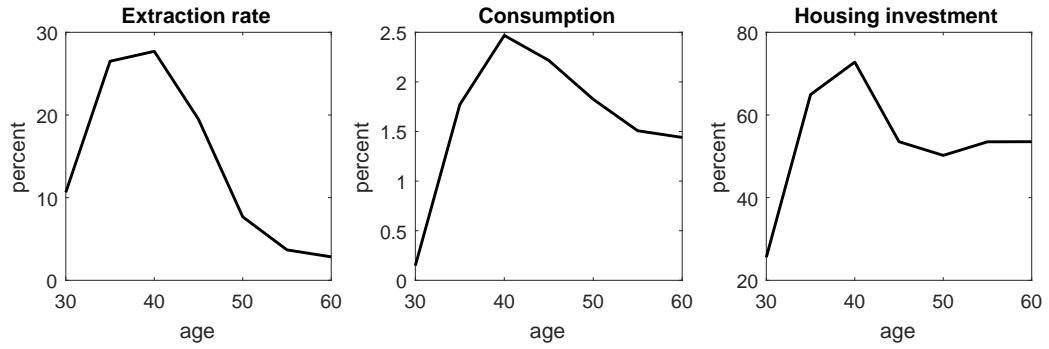
Figure 1.10: Impact responses to a permanent mortgage rate reduction
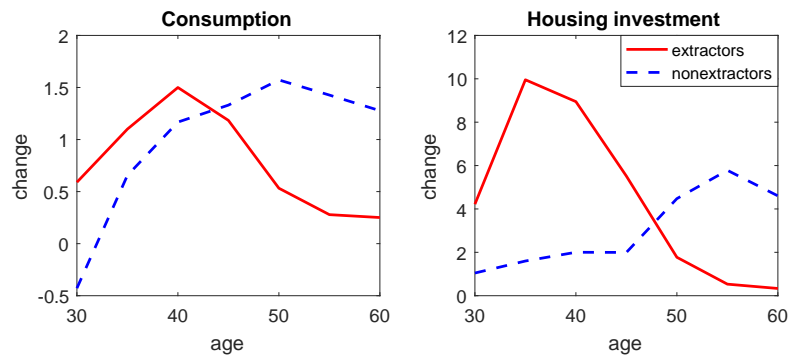
Figure 1.11: Impact responses to a permanent mortgage rate reduction by extraction status
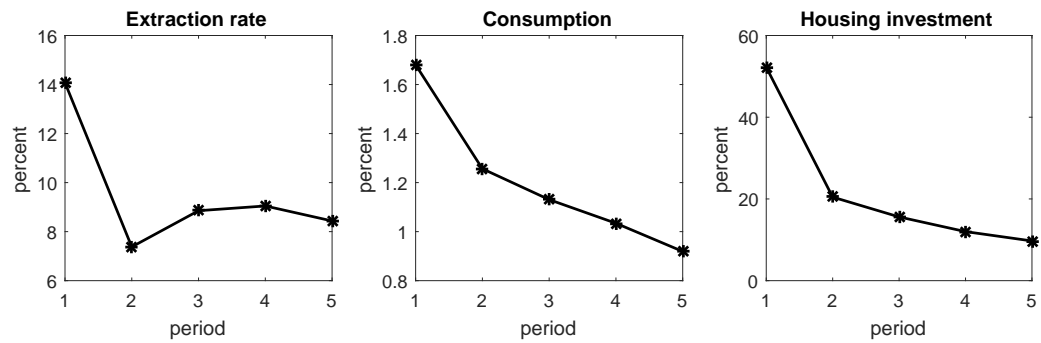
Figure 1.12: Impulse responses to a permanent mortgage rate reduction
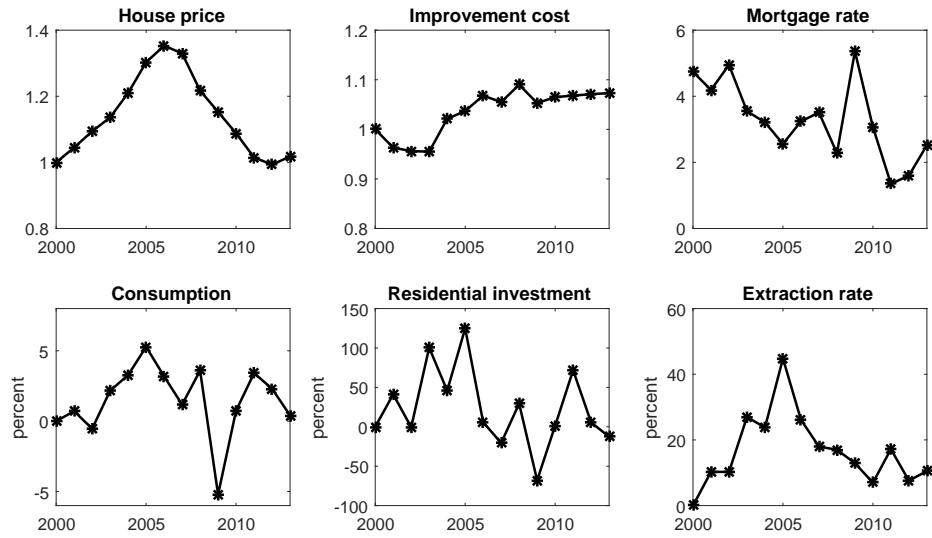
Figure 1.13: The boom-bust cycles in the 2000s

Notes: The upper panel plots historical time series of real house price indexes, real cost indexes for home improvement and building, and real mortgage rates. The lower panel plots model simulated paths (as deviations from the steady state) by feeding the historical series to the model.
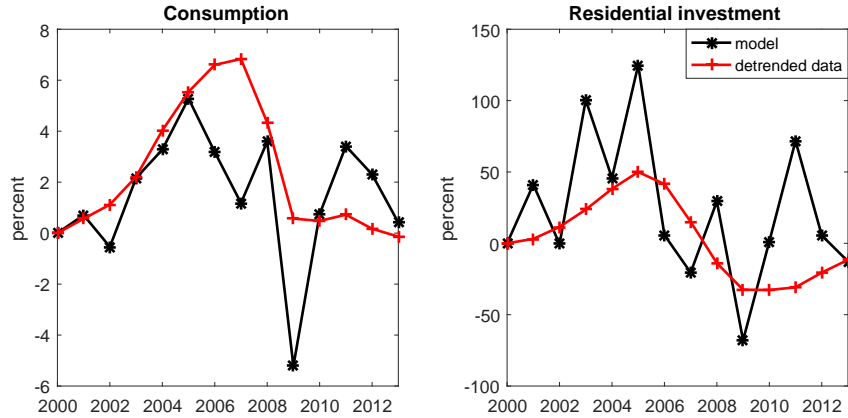
Figure 1.14: The boom-bust cycle in consumption and residential investment

Notes: This figure plots consumption and residential investment simulated by the model, and detrended real personal consumption expenditures and residential investment from NIPA.
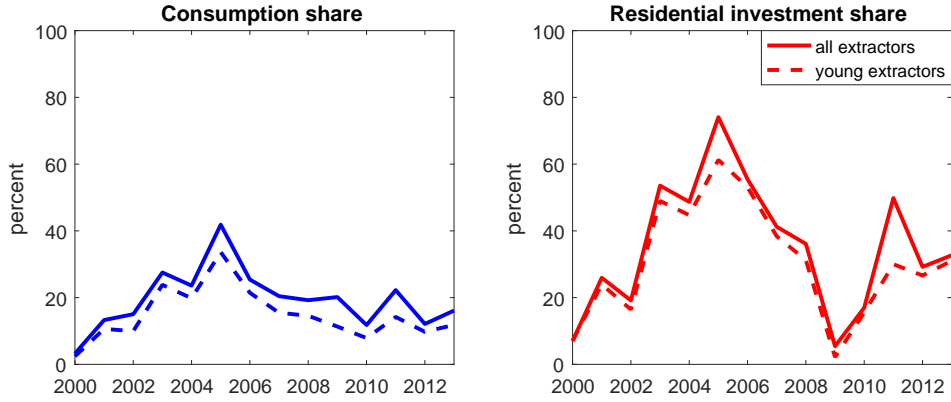
Figure 1.15: Aggregate spending share accounted by home equity extractors

Notes: This figure plots the share of consumption and residential investment expenditures accounted by all home equity extractors and young home equity extractors aged 26 to 45.
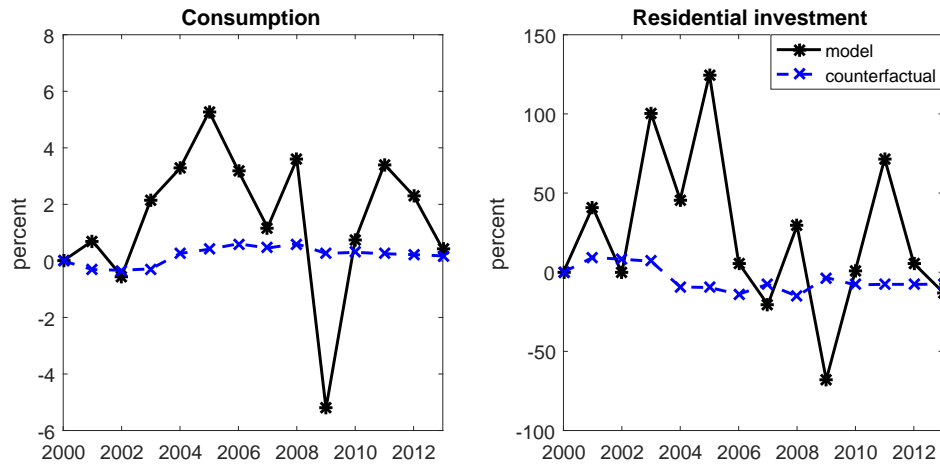
Figure 1.16: The amplification effect of the home equity-based borrowing

Notes: This figure plots consumption and residential investment simulated from the model, and from the counterfactual economy in which collateral borrowing is disabled.

CHAPTER 2

Multiplier Effects of Federal Disaster-Relief Spending: Evidence from U.S. States and Households

2.1 Introduction

The simultaneous sharp decline in consumer spending and income in the United States during the Great Recession of 2007-09 has redirected policymakers' attention to the problem of applying fiscal stimulus in economic downturns. A fiscal stimulus such as higher government spending is particularly useful when the short-term nominal interest rate reaches the zero lower bound. For example, in 2009, the largest economic recovery program in history, known as the American Recovery and Reinvestment Act, was enacted by the U.S. Congress. The motivation behind this monumental spending increase was the Keynesian view that higher government spending creates a multiplier effect on private consumption and income. How effective such policies are and how exactly they accomplish their objective have remained open questions.

Although there is a large literature using household survey data to evaluate the effect of tax rebates and government transfers on private consumption, the literature on evaluating the effect of government spending is much smaller.[1] One strand of this literature has studied the response of U.S. aggregate consumption to government spending shocks. Different empirical approaches in this literature may generate very different estimates of the consumption response. There is not even agreement on the sign of this response. For example, the narrative approach, based on changes in military spending associated with wars, suggests that private consumption decreases.[2] One potential problem with this approach is that, after the 1980s, defense spending has exhibited only moderate variation, unlike during WWII and Korean War, creating a weak instrument problem. The power of

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[1]See e.g., Parker et al. (2013), Sahm et al. (2010), Misra and Surico (2014), Hausman (2016) and Acconcia et al. (2015).

[2]See e.g., Ramey and Shapiro (1998), Ramey (2011), Burnside et al. (2004), Barro and Redlick (2011).

this approach is further weakened by the fact that the share of defense spending in total government spending has shrunk since the 1980s.

Another commonly used approach is structural VAR modeling. This approach tends to find that private consumption increases after a positive spending shock.[3] VAR models often impose a causal ordering of the model variables, in which government spending does not respond contemporaneously to output fluctuations. This assumption, however, is far from obvious during the recent recessions. Alternative structural VAR models of the effect of government spending based on sign restrictions are only set identified, and therefore are difficult to interpret (see Kilian and Lutkepohl (2017)).[4]

Another strand of the literature relies on cross-sectional estimates. Various identification strategies have been proposed to study the multiplier effect based on U.S. state or county-level data using tools developed for the analysis of small open economies.[5] Because private consumption data are typically unavailable at the state or county level, this strand of the literature has necessarily focused on providing estimates on the income and employment effects, rather than the effect on private consumption. The analysis in the current paper circumvents this difficulty by utilizing data from a household-level expenditure survey as well as previously unavailable Bureau of Economic Analysis (BEA) data on state-level private consumption.

I estimate the effect on household expenditure, from an increase in federal government disaster-relief spending in the local area, relative to the expenditure made by households in areas not receiving such spending, holding constant the financial loss from the disaster. These cross-sectional estimates can be interpreted as the consumption response in an "open-economy" setting, where nominal interest rates and tax policies are constant across households and areas.

I construct a measure of disaster-relief spending at the U.S. state level by compiling the government's financial obligations associated with each natural disaster event. Unlike defense spending, disaster-relief spending shows large variation over the last twenty years and varies considerably across states. Compared to the structural VAR approach, the identification in my analysis follows from the fact that the precise timing and the severity of natural disasters are unpredictable, and that the disaster-relief spending is not driven by the local business cycle. To the best of my knowledge, this is the first paper that provides

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[3]See e.g., Blanchard and Perotti (2002), Gali et al. (2007), Monacelli and Perotti (2008), and Fatas and Mihov (2011).

[4]Examples of such models include Mountford and Uhlig (2009), Arias et al. (2016), and Caldara and Kamps (2012).

[5]See e.g., Nakamura and Steinsson (2014), Shoag (2012), Serrato and Wingender (2014), Clemens and Miran (2012), Wilson (2012) and Chodorow-Reich et al. (2012).

direct, cross-sectional evidence for the effect and the transmission channel of government spending shocks on private consumption.

I use detailed household expenditure data from the Consumer Expenditure Survey (CE). The residence identifier in this survey allows me to link the residences of households to the states receiving disaster-relief spending. I find a large, positive private consumption response. One dollar of disaster-relief spending increases total private expenditures by 73 cents. How do we interpret this effect? The previous literature has highlighted three channels by which government spending shocks can affect private consumption. First, as government spending increases, the demand for output rises, which shifts out the derived demand for labor (see e.g., Monacelli and Perotti (2008) and Nakamura and Steinsson (2014)). Hours and real wages increase, and hence consumption. I refer to this channel as the labor demand channel for short. Second, government spending has to be financed. Rational consumers know that current spending is associated with higher future taxes. The spending shock, therefore, represents a negative wealth shock that reduces private consumption (see e.g., Baxter and King (1993)). Third, demand from the government creates inflation. Whether the monetary authority "leans against the wind" by changing the nominal interest rate, therefore, is crucial for determining the consumption response (see e.g., Woodford (2011) and Nakamura and Steinsson (2014)). The advantage of using cross-sectional data is that the last two effects are the same for all households, and are differenced out when including time fixed effects in the estimation. Intuitively, this happens because disaster-relief spending is financed by federal taxes, levied on all households at the same federal tax rate, and because all households in the United States face the same nominal interest rate at any given point of time. Thus, this approach isolates the labor demand channel, and the estimated consumption responses reflect the effect of government spending shocks on labor income.[6]

My analysis provides empirical evidence in support of the existence of the labor demand channel of government spending. If this channel operates, we would expect that households working in disaster-relief related jobs are more affected by disaster-relief spending, and hence exhibit stronger consumption responses relative to other households in the same state. The detailed household information embedded in the CE survey data provides a unique opportunity to uncover the heterogeneous consumption responses across households based on their labor market characteristics. I interact the state disaster-relief spending with a series of labor market characteristics such as occupation, source of income, and

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[6]Note that the real interest rate is not equal across states, to the extent that government spending shocks in one state raise the price level in that state relative to other states. This implies that the real interest rate may fall in the state exposed to the spending shock. The latter inflationary effect reflects changes in the demand for output and hence is part of the labor demand channel.

education. I find that households most likely to work in disaster-relief related jobs, such as firefighters, policemen, and self-employed contractors, experience larger consumption growth relative to other households in the same state, when the state receives disaster-relief spending. This evidence directly supports the existence of the labor demand channel of government spending.

Another way of quantifying the labor demand effect of government spending is to provide an estimate of the income response. While the CE data are known for providing high-quality, quarterly expenditure data, the CE income data are often top-coded, missing, only infrequently reported, and prone to an under-reporting problem. Given the limitations of the household-level income measures in the CE survey, I complement my analysis with a second set of results based on state-level data. I use a recently released, but previously unavailable state-level personal consumption expenditure data set provided by the U.S. BEA to estimate the consumption effect of disaster-relief spending at the state level. The state-level estimates are quantitatively similar to the household-level estimate. One dollar of disaster-relief spending increases private consumption expenditures by 78 cents. I then estimate the income effect using state output and personal income measures. The income multiplier is about 1.8, consistent with cross-sectional estimates in the literature that range from 1.5 to 2. Finally, using state-level employment data, I estimate that one million dollars of disaster-relief spending create 8 nonfarm jobs.[7] The industries experiencing the highest employment growth are construction (3 jobs) and support, waste management, and remediation services (1.6 jobs), which are industries highly involved in disaster-relief activities.[8]

My analysis, therefore, supports the theory that government spending shocks can have a large effect on consumption and income, and that this effect operates through the labor market. My estimate represents the aggregate consumption response when monetary policy

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[7]This estimate is close to that obtained by Wilson (2012) based on data from the American Recovery and Reinvestment Act. For a similar estimate, see also Chodorow-Reich et al. (2012).

[8]In related work, Fidrmuc et al. (2015) study the impact of natural disasters on state government spending and income. They propose using economic damages due to natural disasters as an instrument to estimate the causal effect of government spending on personal income in a recursively identified vector autoregressive model including damages, state government spending, and personal income in that order. Their estimates of the multiplier effect have to be viewed with caution, however. The key difference from my work is that they estimate the effect of natural disaster damages, rather than the effect of government spending, as claimed by the authors. Their damages variable is not a valid instrument for government spending because it directly affects the local economy and hence personal income (for example, by destroying public infrastructure and household durable goods). In other words, the exclusion restriction for a valid instrument is violated. Replacing the state's own damages with the damages in nearby states in the model does not solve this identification problem. Moreover, the authors determine the damages in each state based on the proportion of FEMA's spending on that state. As I show in Section 2.3, FEMA's spending on one state is not proportional to the disaster damages in that state.

is accommodative and the expected taxes do not change. An interesting question is whether the effect of government spending varies over the business cycle. There is no consensus in the recent empirical literature on the effect of the government spending during recessions.[9] Using evidence from disaster-relief spending, I find that the private consumption response is significantly smaller in states with rising unemployment rates, consistent with the view that households are less responsive in bad times.

One potential concern with using data on disaster-relief spending, as opposed to military spending, is that natural disasters may systematically affect private consumption due to the financial loss brought about by the disaster itself.[10] Hurricanes, for example, may destroy vehicles or furniture, and the owners may have to spend money to replace destroyed consumer durables. Thus, I may overestimate the consumption effect of disaster-relief spending by attributing the replacement expenditures to the government spending effect. I address this problem by controlling for the financial losses due to natural disasters. The identifying assumption is that, conditional on the financial loss from disasters, the variation in government disaster-relief spending is exogenous to the expenditures of the households in the affected area.

Finally, the detailed expenditure data in the survey allow me to distinguish which expenditure component contributes most to the total expenditure response. I find that expenditures on durables and, in particular, purchases of new vehicles, account for most of the consumption response. The increase in expenditures on durables is almost eight times that of nondurables. I construct a partial-equilibrium consumer choice model to interpret this large differential response. The model shows that, when government spending creates labor demand and increases household income, consumer spending on durables and nondurable consumption increase proportionately. Since the stock of durables is large, a proportionate increase in both types of consumption implies much larger expenditures on durables. In the calibrated consumer choice model, the ratio of the response of durable over nondurable goods expenditures is quantitatively similar to the ratio estimated based on the survey data.

The remainder of the paper proceeds as follows. Section 2.2 describes the data. Section 2.3 discusses the identification problem in estimating the effect of disaster-relief spending on private consumption, and proposes a novel solution for addressing this problem. Section 2.4 describes the empirical specifications. Section 2.5 presents household-level evidence

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[9]See e.g., Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Barro and Redlick (2011), Nakamura and Steinsson (2014), and Ramey and Zubairy (2014).

[10]This does not mean that defense spending associated with major wars is necessarily exogenous. Interactions with the tax codes, price controls, patriotism, and changes in other macroeconomic variables can confound this spending effect.

on the consumption stimulus. Section 2.6 complements the household-level analysis by examining the income and employment multipliers. Section 2.7 presents a standard consumer choice model that helps us to interpret the differential response found in Section 2.5. Section 2.8 concludes.

2.2 Data

In the United States, the federal government provides disaster-aid assistance through the distribution of disaster-relief funds, which are largely managed by the Federal Emergency Management Agency (FEMA). Not every disaster incident is funded. The Stafford Act specifies the conditions and requirements for an event to be declared a major disaster or an emergency. Only declared disasters and emergencies receive funding for relief. Figure 2.1 illustrates the Stafford Act procedure for a disaster event to receive FEMA's financial aid.

When a disaster is declared, the affected state can receive funds through three FEMA-supported programs. The public assistance program, FEMA's largest funding program, provides funds for emergency management, removing debris, and repairing or rebuilding public structures. The hazard mitigation program provides funds for working projects that prevent or mitigate future hazards. The individual and household assistance program provides temporary housing, counseling, and loss compensation.

I obtain the federal government's financial obligations under each of the three programs for each disaster that occurred after the year 2000 by accessing the OpenFEMA data sets.[11] These data sets provide a detailed description for each declared disaster including the timing, location, incident type, funding recipients, federal obligation amount, etc. Disaster funding records before the year 2000 are provided by Russell Sobel (see Garrett and Sobel (2003)).

Based on the timing and location of each disaster, I aggregate the funding information to the state-month level to construct a disaster-relief spending variable. At the national level, disaster-relief spending shows large variation over time, as shown in Figure 2.2. Spikes are often caused by a single event in that year, as was the case after the Northridge earthquake in 1994, after September 11 in 2001, after Hurricane Katrina in 2005, and after Hurricane Sandy in 2012. The spending also exhibits large variation across states. Figure 2.3 shows the twenty states that received most disaster-relief spending between 1989 and 2014. Within each state, there is large variation in disaster-relief spending over time. Figure 2.4 shows the monthly funding amount for the six largest state recipients. Almost

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[11]www.fema.govdata-feeds (accessed in August 2015).

all declared disasters are natural disasters, with storms and hurricanes the most frequently occurring types, as shown in Figure 2.5.

My primary data source for household consumption is the Consumer Expenditure Survey (CE). Sampled to be representative of the U.S. civilian non-institutional population, the CE data provide information on the purchasing habits of American consumers. I use the quarterly interview survey data, which sample roughly 7,000 consumer units each quarter. Each consumer unit is interviewed every three months over five quarters, which creates a rotating panel. The initial interview collects information on demographics and consumer durable stocks. The following four interviews collect detailed expenditure information over the previous three months. Income and employment data are collected in the second and fifth interview. A limited number of asset-related questions are asked in the fifth interview.[12] The results for the household-level analysis are based on the CE data from 1993 to 2014. I obtain data for 1996 onward from the CE public-use microdata of the Bureau of Labor Statistics (BLS). Data before 1996 are obtain from the ICPSR at the University of Michigan.

Consumer units that meet one or more of the following conditions are excluded from the empirical analysis: (i) missing state identifier; (ii) moved at least once during the sample period; (iii) incomplete income report; (iv) at the bottom one percent of food expenditures.

I also utilize data on state-level consumption. The BEA recently for the first time released estimates of personal consumption expenditures by state for the years 1997 to 2014. These consumption data are constructed to be consistent with the consumption data in the national income and product accounts. State GDP and personal income measures are obtained from the BEA regional accounts. State-level seasonally adjusted unemployment rates and employment by major industry are obtained from the BLS. State populations and the number of households in the United States are from the Census Bureau. Finally, I obtain the seasonally adjusted CPI from the FRED database.

To control for the financial losses from natural disasters, I obtain estimates of the state-level property losses caused by natural disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) at monthly frequency. These loss data are constructed from the hardcopies and the electronic database of the National Climate Data Center's storm data records. These records combine the information from public and private insurance programs, and various government agencies, to form estimates of the

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[12]The CE data consist of two independently sampled surveys. One is the quarterly interview survey. The other is the diary survey. The diary survey collects household expenditure data through self-reported daily records for up to two consecutive weeks. I use the interview survey data, which, shown by Bee et al. (2012), better match the national account data.

financial losses from natural disasters.[13]

2.3 An Empirical Strategy for Dealing with Endogeneity

One advantage of using the government's spending on disaster relief to estimate the response of private consumption is that such spending is unlikely to be driven by local economic conditions, but more likely to be determined by geographic or climatic conditions. Even though certain areas are more vulnerable to a specific type of natural disasters, the precise timing of disasters is hard to predict. This creates exogenous variation in the timing of the relief funds.

However, there are other concerns with using this type of spending. Natural disasters may have additional direct impacts on household expenditures and on the local economy. For example, hurricanes may destroy consumers' durable stock (e.g., furniture and vehicles). Owners may spend money to replace these damaged goods. If replacement expenditures are made at the time when the state receives disaster-relief funds, one may overestimate the effect of disaster-relief spending. At the same time, natural disasters may have negative economic impacts due to the destruction of public infrastructure (e.g., buildings, roads, and the power supply) or due to fatalities. This may cause an underestimation of the effect on private consumption. The latter negative economic impacts of natural disasters are likely to be a less concern in practice because they tend to be short lived. Noy (2009), however, shows that natural disasters have a statistically significant effect on property damaged, which has to be taken into account in estimating the effect of disaster-relief spending on consumption.

Thus, the effect of disaster-relief spending on private consumption can only be identified if the confounding impacts brought about by the natural disaster are controlled for. Given that households in the CE survey do not report property damages from natural disasters, my approach is to control for the "average" amount of the damaged properties in the affected area. Consider the following regression specification,

$$\triangle c_{ist} = \alpha_0 + \alpha_1 G_{s,t} + \alpha_2 d_{ist} + \varepsilon_{ist} \qquad (2.1)$$

where $\triangle c_{ist}$ denotes the change in the total expenditures from period $t-1$ to t of household i living in state s. $G_{s,t}$ is the disaster-relief spending received by state s in period t (converted to dollars per household). d_{ist} is the amount of damaged properties for household i living

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[13]There are a few caveats about the loss data constructed by SCHELDUS. First, only when a loss amount is estimated to be above \$50,000, the loss amount is recorded. Second, when a range of loss estimates is received for the same event, SCHELDUS uses the lower bound.

in state s in period t due to the local disasters.

If d_{ist} is precisely measured for each household, then α_1 captures the multiplier effect of disaster-relief spending on household expenditures, and α_2 captures the impact of the disaster itself on household expenditures through the amount of the damaged properties. However, d_{ist} is not observed in the data.

One solution is to control for the "average" amount of the damaged properties in the affected area. d_{ist} can be decomposed into an average loss component and an individual loss component:

$$d_{ist} = D_{s,t} + (d_{ist} - D_{s,t}) \equiv D_{s,t} + \tilde{d}_{ist} \tag{2.2}$$

where $D_{s,t}$ is the average property loss amount across households in state s in t. $\tilde{d}_{ist}$ is household i's deviation from the state average. Two assumptions are required to identify α_1.

Assumption 1 *Conditional on the state average property loss $D_{s,t}$, $\tilde{d}_{ist}$ is a mean-zero idiosyncratic loss shock for household i in state s at time t, i.e.,*

$$\mathbb{E}(\tilde{d}_{ist}|D_{s,t}) = 0.$$

Assumption 2 *There exists an exogenous component in the government's disaster-relief spending that is not driven by the average loss amount or the idiosyncratic loss shock, i.e.,*

$$G_{s,t} = \beta D_{s,t} + g_{s,t} \quad and \quad D_{s,t} \perp\!\!\!\perp g_{s,t}, \quad \tilde{d}_{ist} \perp\!\!\!\perp g_{s,t}|D_{s,t}, \tag{2.3}$$

where $\perp\!\!\!\perp$ denotes stochastic independence.

Substituting equations (2.2) and (2.3) into (2.1) yields

$$\triangle c_{ist} = \alpha_0 + \alpha_1 g_{s,t} + (\alpha_1 \beta + \alpha_2)D_{s,t} + v_{ist} \tag{2.4}$$

where $v_{ist} \equiv \alpha_2 \tilde{d}_{ist} + \varepsilon_{ist}$. Under Assumptions 1 and 2,

$$\mathbb{E}(v_{ist}|g_{s,t}, D_{s,t}) = 0 \quad and \; \alpha_1 \; is \; unbiased.$$

Note that Assumptions 1 and 2 also imply that $\mathbb{E}(v_{ist}|G_{s,t}, D_{s,t}) = 0$. By rearranging equation (2.4), an unbiased estimate of α_1 can be obtained by estimating the regression model,

$$\triangle c_{ist} = \alpha_0 + \alpha_1 G_{s,t} + \alpha_2 D_{s,t} + v_{ist}.$$

The exogeneity assumption, Assumption 2, is not an unrealistic assumption. Garrett

and Sobel (2003) find evidence for political bias in the allocation of FEMA disaster-relief funds. Specifically, they show that disaster-relief spending is higher in the states having more congressional representatives in the congressional committees that oversee FEMA.[14] Eisensee and Stromberg (2007) demonstrate that mass media have a strong influence on whether, and how fast, the U.S. government responds to foreign disasters, which, to some extent, may reflect the government's attitude toward domestic disasters. Finally, a large number of retrospective reports and post-event evaluations show that FEMA and other government agencies often misjudge the damage caused by disasters.[15]

To measure the exogenous variation in disaster-relief funds, I regress $G_{s,t}$ on $D_{s,t}$ at the monthly frequency from 1989 to 2014, and include time and state fixed effects. The residuals from this regression measure the component in disaster-relief spending that is not related to the damages caused by the disaster. The R^2 is 0.7 when using the full sample, but falls to 0.3 when I exclude Hurricane Katrina.[16] This shows that factors, other than the loss amount, play an important role in determining the amount of disaster-relief spending.

2.4 Empirical Specifications

This section describes the empirical models used for estimating the effects of disaster-relief spending. At the household level, I estimate the average effect of disaster-relief spending on household expenditures, the heterogeneous effects across households based on their labor market characteristics, and the differential expenditure responses over the local economic cycle. At the state level, I estimate the consumption, income and employment effect of disaster-relief spending.

2.4.1 Household-level Analysis

To estimate the response of total private expenditures (or the response of an expenditure component), I estimate the following regression model,

$$\triangle c_{ist} = \alpha_0 + \alpha_1 G_{s,t} + \alpha_2 D_{s,t} + \mathbf{x}_{ist}\eta + \gamma_s + \delta_t + \nu_{ist} \tag{2.5}$$

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[14]Such politics-driven spending can also be observed in response to other incidents. For example, in October 2012, when Hurricane Sandy hit the East coast, New York and New Jersey suffered almost the same amount of damages, but New York received nearly seven times more FEMA funds than New Jersey. Some argue that this is due to the New York lawmakers' successful lobby. See *Why New Jersey Got Billions Less than New York in FEMA Disaster Aid After Sandy*, by Scott Gurian in 2015.

[15]See e.g., *FEMA makes a $12 million mistake on Iowa flood*, by S. Westwood in 2014, and *A Failure of Initiative*, by the U.S. House of Representatives in 2006.

[16]I exclude the samples from Louisiana, Alabama, Mississippi, and Florida in August and September 2005.

where $\mathbf{x}_{ist}$ is a vector of household characteristics that capture demographic features, financial conditions, and whether the household purchased a vehicle and/or homeowner's insurance in the previous period. γ_s is a state-fixed effect that controls for the time-invariant heterogeneity across state, such as geographic and climatic conditions. δ_t is a time fixed effect that controls for aggregate conditions that affect household expenditures and income such as tax policies and interest rates. Household expenditures are converted to 2005 dollars using the CPI. $G_{s,t}$ and $D_{s,t}$ are converted to 2005 dollars per household. Other variables are defined in Section 2.3. In the household-level analysis, standard errors are clustered at the household level.[17]

Intuitively in model (2.5), the disaster-relief spending effect is estimated by comparing households in the states receiving disaster-relief spending with households in the states not receiving such spending. In the next model, I estimate the differential effect across households within the same state. Households have different responses because they have different labor market characteristics, which expose them differently to the labor market impact of disaster-relief spending.

To estimate such heterogeneous responses across households, I interact the disaster-relief spending variable with a household-specific characteristic:

$$\triangle c_{ist} = \alpha_0 + \alpha_1 G_{s,t} + \alpha_2 D_{s,t} + \alpha_3 G_{s,t} \times I(A)_{ist} + \mathbf{x}_{ist}\eta + \gamma_s + \delta_t + \nu_{ist} \tag{2.6}$$

where $I(A)_{ist}$ is an indicator variable equal to 1 if a condition A is met by household i in state s at time t, and zero otherwise. In this model, the total effect of disaster-relief spending is $\alpha_1 + \alpha_3 I(A)_{ist}$.

To see whether the effect of disaster-relief spending varies over the local business cycle, I interact the disaster-relief spending variable with the change in the local unemployment rate, a proxy for local business cycles. The estimated model is

$$\triangle c_{ist} = \alpha_0 + \alpha_1 G_{s,t} + \alpha_2 D_{s,t} + \alpha_3 G_{s,t} \times \triangle U_{s,t} + \alpha_4 \triangle U_{s,t} + \mathbf{x}_{ist}\eta + \gamma_s + \delta_t + \nu_{ist} \tag{2.7}$$

where $\triangle U_{s,t}$ is the change in the unemployment rate from time $t-1$ to t in state s. α_1 is the effect of disaster-relief spending in the states that have a zero unemployment rate growth. α_3 captures the additional effect of disaster-relief spending of a one percent increase in the state-level unemployment rate.

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[17]Alternative, one could cluster at the state level. In the latter case, the key regression results are statistically significant not only at the 5% level, but at the 1% level.

2.4.2 State-level Analysis

Following the previous literature on estimating the multiplier effect of government spending from cross-sectional state-level data, I estimate the consumption and income effect at the state-level by

$$\frac{\triangle C_{s,t}}{Y_{s,t-1}} = \theta_0 + \theta_1 \frac{G_{s,t}}{Y_{s,t-1}} + \theta_2 \frac{D_{s,t}}{Y_{s,t-1}} + \gamma_s + \delta_t + u_{s,t} \tag{2.8}$$

$$\frac{\triangle Y_{s,t}}{Y_{s,t-1}} = \zeta_0 + \zeta_1 \frac{G_{s,t}}{Y_{s,t-1}} + \zeta_2 \frac{D_{s,t}}{Y_{s,t-1}} + \gamma_s + \delta_t + \epsilon_{s,t} \tag{2.9}$$

where $\triangle C_{s,t}$ and $\triangle Y_{s,t}$ denote the change in personal consumption expenditures and income from year $t-1$ to t in state s. $Y_{s,t-1}$ denotes the income in state s in year $t-1$. Disaster-relief spending, consumption, income and property losses are converted to 2005 dollars using the CPI and then normalized by state population.

For employment, I estimate the number of jobs created by one million dollars of disaster-relief spending. The regression model is

$$\triangle L_{s,t} = \xi_0 + \xi_1 G^m_{s,t} + \xi_2 D^m_{s,t} + \gamma_s + \delta_t + \upsilon_{s,t} \tag{2.10}$$

where $\triangle L_{s,t}$ denotes the change in the employment. $G^m_{s,t}$ and $D^m_{s,t}$ denote real disaster-relief spending and property losses expressed in million dollars. Employment, disaster-relief spending and property losses are normalized by state population.

2.5 Household-Level Evidence

This section presents household-level evidence for the effect of disaster-relief spending. First, I show that disaster-relief spending on average increases total household expenditures, especially expenditures on durables. Then I provide evidence to support the labor demand channel of government disaster-relief spending. I show that the increase in private expenditures has significant heterogeneity across households based on their labor market characteristics. In particular, I find that households most likely to work for disaster-relief related jobs have the largest consumption response. Finally, I use the government's disaster-relief spending to study whether the effect of government spending is larger when the local economy has slack, and my result shows the opposite.

2.5.1 Does Private Consumption Respond to Disaster-Relief Spending?

Throughout my analysis, I exclude households interviewed during the Hurricane Katrina months: September 2005 to February 2006.[18] All regressions control for demographics (the household head's age, gender, race, education, the family size and its change, the number of adults and its change), the household's income ranking in the previous year, and indicators of whether the household purchased a car and/or homeowner insurance in the previous quarter.

Table 2.1 shows the response of total private expenditures. Column (1) shows that, without controlling for the property loss, one dollar of disaster-relief spending, on average, increases total private expenditures by 84 cents. As discussed in Section 2.3, this may cause us to overestimate the spending effect by attributing the replacement expenditures made by households in response to disaster damage to the government spending effect. In column (2), I include the state average property loss, and the estimate falls to 70 cents. Including the full amount of losses may cause us to overestimate the loss impact, given that most households purchase insurance, and can receive compensation if loss occurs.[19] In the extreme case where everyone's loss is fully covered by insurance, the coefficient in column (1) actually reflects the true disaster-relief spending effect. To account for the fact that property losses may be partially compensated by insurance policies, in column (3), I replace the loss measure by an adjusted loss measure. This adjusted loss measure is constructed by multiplying the loss $D_{s,t}$ by the share of the households in the state that neither purchased car nor homeowner insurance in the previous quarter. This is the preferred specification, and the coefficient on disaster-relief spending gives the baseline estimate, 73 cents. Column (4) includes lagged spending to capture the dynamic effect of disaster-relief spending, but this effect is insignificant.

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[18] There are two reasons for removing the Katrina event. First, Hurricane Katrina, one of the deadliest and costlier natural disasters in the U.S. history, has caused severe destruction and permanent impacts to the affected areas. Affected households experienced a permanent income change, migration, and health and psychological problems. These impacts brought by the disaster itself, as discussed in Section 2.3, on household expenditures cannot be simply controlled for by including the property loss measure in the estimation. Second, the spending data provided by FEMA are associated with specific events. This means that the dates I used to identify the timing of the funding may not be the timing when the funds are obligated. For example, funds obligated in 2010 for Katrina relief are recorded as August 2005 funding, the time when the Katrina event was declared. This is not an issue for moderately sized events, because funds are distributed quickly after the event, and because rational consumers respond to changes in expectations. In the Katrina event, this was not the case. Relief funds were obligated months or years after the event was declared, and it is not clear whether the ex-post relief funds were expected by households.

[19]In the CE data, 66 percent of homeowners pay homeowner insurance, and 65 percent of car owners pay auto insurance.

Table 2.2 decomposes the effect of disaster-relief spending on private consumption expenditures by estimating the response of different expenditure categories. In the left panel, I start by estimating the response of food and beverages. This response is almost zero. I then estimate the effect on all other nondurable expenditures (e.g., tobacco, utility, house operation, gas, personal care, etc.). The response is small, only a 9-cent increase, and is insignificant. However, expenditures on durables (housing equipment, entertainment, education and vehicle purchases) increase by 65 cents, accounting for almost 90 percent of the total expenditure increase. Given the large response of expenditures on durables, I then estimate the response of each durables category. The results are shown in the middle panel. The expenditures on vehicles alone explain a 55-cent increase. Finally, using detailed information on vehicle purchases in the CE survey, I estimate that new vehicle purchases account for the bulk of expenditure growth, a 50-cent increase, as shown in the right panel.[20]

There are two interesting questions left from the results in Table 2.1 and 2.2. First, how do we explain the positive consumption response to disaster-relief spending? Second, why do expenditures on durables respond much more than expenditures on nondurables? I provide the answer to the first question in Section 2.5.2 and Section 2.6. The second question is answered in Section 2.7, where I set up a partial-equilibrium consumer choice model with durable and nondurable goods to interpret the large differential response between the expenditures on durables and nondurables.

2.5.2 Why Does Private Consumption Respond to Disaster-Relief Spending?

The estimates in Tables 2.1 and 2.2 show that unexpected increases in disaster-relief spending increase private consumption. As discussed in introduction, this effect may be explained based on three mechanisms. First, in New Keynesian models, there is a labor demand channel. Government spending shocks represent labor demand shocks, to the extent that households are hired to produce output purchased by the government. The increased labor income then boosts private consumption. Second, rational consumers know that the current spending is associated with higher future taxes. The spending shock hence creates a negative wealth effect that reduces private consumption. Third, the

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[20]One potential concern for such a large estimated response in vehicle purchases is that some households may finance their vehicle purchase by an auto loan, and hence the reported expenditures on the vehicle have not been fully made. The CE data also provide adjusted vehicle expenditures that account for the debt-financed purchases (expenditures include down payment, principal and interest paid on loans, and the purchase amount if the vehicle is not financed). The results from using the adjusted expenditure variables are almost the same as in Table 2.2.

increased demand from the government creates inflation. Whether the monetary authority "leans against the wind" by changing the nominal interest rate matters for the consumption response. The advantage of using cross-sectional estimation is that the last two effects are the same for all households, and are differenced out by including time fixed effects. Thus, this approach isolates the labor demand channel, and the estimated consumption responses reflect the effect of government spending shocks on labor income.

In this section, I provide direct empirical evidence in support of the existence of the labor demand channel of government disaster-relief spending. If this channel operates, we would expect that households working for disaster-relief related jobs are more affected by disaster-relief spending, and hence have stronger consumption responses relative to other households in the same state. I examine households' expenditure responses based on a number of labor market characteristics, including occupation, income source and education. Table 2.3 shows the results for the heterogeneous response across all 18 occupations defined by the BLS. The comparison group is households whose head is not working. The expenditure response of the latter group is not significant. The coefficient of the interaction term represents the differential effect of disaster-relief spending on households' expenditures relative to the comparison group. The five most responsive occupations, ranked by total expenditure growth, are grounds keeping, protective services, armed forces, repairers and technician. The total expenditure response of the households working for protective services (e.g., firefighters, policemen, security guards) and armed forces (e.g., emergency and disaster-relief management, army engineers, protective services) is statistically significant at the 10 percent level. The results for expenditures on durables and new vehicle purchases show a similar ranking by occupation. These results are expected because these are the jobs or industries most relevant to disaster-relief activities, and workers hired for these jobs benefit from government disaster-relief funds.

Next, I study the heterogeneous response across households based on their income source. The interaction term is the employer from which the household head received most earnings in the past year. The results in Table 2.4 show that households with a self-employed head experience the largest expenditure growth. This is easy to explain. The types of work funded by FEMA for disaster relief usually include emergency management, removing debris, and repairing or rebuilding public structures, which are likely to be short-term jobs targeted at self-employed workers.

Table 2.5 shows the heterogeneous response across households based on the household head's education level. While other levels of education show almost no difference or a smaller response than the benchmark households who have one to eight years of education, households with the head having an above-high-school/occupational/associate

degree experience higher expenditure growth. Based on the BLS website, most jobs in protective services and emergency management require an entry-level educational degree to be high school. Since workers in these industries usually receive on-the-job professional training, they would report their education at an above-high-school/occupational/associate level. Thus, this result is consistent with the evidence from household occupations.

Another way of showing the labor demand effect of disaster-relief spending is to provide an estimate of the income response. However, there are several issues with the CE income data that complicate the estimation of this response. First, income information in the CE data is top-coded, missing, infrequently reported, and prone to an under-reporting problem. Second, income and expenditures are reported for different time periods, which makes the response of income and consumption noncomparable. Figure 2.6 illustrates this problem. For example, a household first interviewed in January 2001 will continue to be interviewed every three months until January 2002. In each interview, the household reports its expenditures for the previous three months, but reports its income only in the second and fifth interview, and the two income reports are for the past 12 months. Because of this interview design, the change in consumption cannot be mapped into the change in income for the same period.

Given these limitations in the household-level income measures, in Section 2.6, I complement my analysis with state-level data. I provide estimates of the income response using state output and personal income. Before turning to this analysis, the next subsection investigates the dependence of the consumption response estimates on the state business cycle.

2.5.3   Is the Consumption Response Larger When the Local Economy Has Slack?

The standard Keynesian view suggests that the multiplier effect of government spending shocks is larger during periods of economic slack. The argument is that the economy operates below capacity in this case, and that the monetary and tax policies tend to be accommodative during recessions. The empirical evidence for this argument is mixed. Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012), for example, find a larger output multiplier during economic recessions by estimating a structural VAR model. Nakamura and Steinsson (2014) and Shoag (2012) only find moderate evidence for a larger multiplier effect during recessions based on state-level cross-sectional regressions. Ramey and Zubairy (2014) find no evidence for a state-dependent multiplier when studying military spending data. Berger and Vavra (2014) find a larger durable expenditure response

during normal times, rather than in recessions. Since policymakers tend to use fiscal stimulus more frequently during recessions, examining whether government spending can generate a larger multiplier effect in these times is important.

In this section, I provide evidence on how the consumption response of disaster-relief spending depends on local economic conditions. My results are based on household expenditures and show that the effect of a government spending shock is smaller during times of economic slack. Table 2.6 shows the results from estimating equation (2.7), where disaster-relief spending is interacted with the change in the state-level unemployment rate. In the states that have no change in the unemployment rate, private total expenditures increase by 73 cents, similar to the average response in Table 2.1. As the unemployment rate increases by one percentage point, the response of total expenditures to disaster-relief spending falls by 1.37 dollars. This implies that, a one standard deviation increase in unemployment rate growth (0.35 percentage points) would reduce the government spending effect to 25 cents. The estimates for durable expenditures and new vehicle purchases, in particular, suggest that consumer spending on durables is less responsive to government spending shocks when the local economy is slack.

These results suggest a smaller government spending effect on private consumption in periods of economic slack. Berger and Vavra (2015) recently proposed a theoretical framework for understanding the sluggish response of durable expenditures to economic shocks during recessions. The key intuition is that microeconomic frictions, amplified during recessions, reduce the frequency of households' adjustment of durables purchases. This may help explain my empirical findings.

2.6   State-Level Evidence

The analysis in Section 2.5 suggests that disaster-relief spending increases private consumption, as government spending increases the demand for labor. Increased labor income boosts private consumption, which is expected to raise aggregate income and employment in a New Keynesian model. It is important to provide direct evidence on the income and employment effect of disaster-relief spending. Because of the limitations in the household-level income measures discussed in Section 2.5, this section estimates the income and employment effect based on state-level data. The BEA publishes output and income measures at the state level, and the BLS publishes employment statistics for major industries at the state level.

I first verify whether the private consumption effect found in the household-level data still exists in the state-level data. I use the BEA's recently released, but previously

unavailable state-level personal consumption expenditure (PCE) data to estimate the consumption effect at the state level. Table 2.7 shows the results by estimating equation (2.8). Column (1) shows that one dollar of disaster-relief spending increases total PCE by 62 cents. The PCE in column (1), however, includes expenditures made by both households and nonprofit organizations. Since expenditures in the household survey are measured only by the consumer's out-of-pocket expenditures, column (2) excludes the expenditures made by nonprofit organizations. The estimated private consumption response is 78 cents, and very similar to the earlier household-level estimate. The last three columns decompose the effect on total private consumption into the response of nondurables, services and durables. This decomposition does not generate the same pattern as in the household-level analysis, possibly because of different definitions for these expenditure categories.[21]

Next, I estimate the income effect of disaster-relief spending. Table 2.8 shows the estimates of equation (2.9). Column (1) shows that one dollar of disaster-relief spending increases output by 2.2 dollars. Column (2) shows that the income multiplier is 1.8. These multiplier effects are consistent with the recent empirical literature using cross-sectional state or county data. Since personal income includes transfers from the government, one could argue that the effect on personal income may be driven by direct transfers from the government to households that compensate for property losses due to disasters, rather than increased demand for labor. Column (3) addresses this concern by excluding these transfers from personal income. The result is the same. This result is not surprising, given that transfers consist of social security benefits, medical benefits, unemployment insurance compensation, veterans' benefits, and income maintenance benefits. Only the last item might be affected by a disaster, and that item only accounts for about 15% of total transfers received. Finally, natural disasters may directly affect farm income because of the sensitivity of agricultural products to weather and climate changes. Therefore, including farm income may confound the multiplier effect with the disaster damage effect. In column (4), I show that excluding farm income increases the personal income response to disaster-relief spending to 1.88 dollars.

Finally, I provide evidence showing that disaster-relief spending increases state employment, especially in the relevant industries. Table 2.9 shows the estimates of equation (2.10). The job multiplier, measured by the number of jobs created by one million dollars of government spending, is 8 for nonfarm payroll employment. This estimate is close to estimates of the job multiplier based on alternative natural experiments (see Wilson (2012) and Chodorow-Reich et al. (2012)). The goods sector gains 4.6 jobs, and the service sector

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[21]See Bee et al. (2012) for a discussion of the definitional differences between CE surveys and PCE in NIPA.

gains the remainder. The industries that have the largest employment gains are construction (3 jobs), and support, waste management, and remediation services (1.6 jobs). Consistent with evidence from the household-level data, these industries provide the jobs most relevant for disaster relief, and hence experience the strongest employment growth.

My household-level and state-level analysis shows that government spending shocks can have large effects on consumption and income, and that these effects arise because the government creates labor demand. One contribution of my paper is that it provides direct evidence in support of such an effect based on household-level survey data that reveal information about households' labor market characteristics. This fact helps me to identify the labor demand channel, which is not feasible in studies based on aggregate data.

2.7 Why Do Expenditures on Durables Respond Much More than Expenditures on Nondurables?

Another question raised by the household-level results is why expenditures on durables respond much more to government spending shocks than expenditures on nondurables. Based on the estimates in Table 2.2, the change in the expenditures on durables is almost eight times that of the expenditures on nondurables. Addressing this question requires a theoretical model. In this section, I construct a partial-equilibrium consumer choice model with both durable and nondurable goods to interpret this differential response.

There are several features of this model. First, government spending affects a consumer's decision through its effect on household income. Government spending shocks represent positive income or wealth shocks. Second, taxes and the real interest rate are assumed constant for simplicity. Third, consumers are rational and are lifetime-utility maximizers. Fourth, the utility function takes the Cobb-Douglas form.[22] Under these conditions, a government spending shock induces a much larger response of the expenditures on durables than nondurables.

Household i living in state s maximizes its expected lifetime utility, subject to the budget constraint, and the law of motion for durable stocks. (I suppress superscripts i and s from now on.)

$$\sum_{j=0}^{\infty} \beta^j E_t U\left(c_{t+j}, d_{t+j}\right)$$

$$s.t. \quad c_{t+j} + x_{t+j} + a_{t+j} = y_{t+j} + (1+r)a_{t+j-1} + (G_{t+j} - T)$$

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[22]Evidence from micro data tends to find an elasticity of substitution close to one.

$$s.t. \quad d_{t+j} = x_{t+j} + (1-\delta)d_{t+j-1}$$

where c_t and d_t denote nondurable consumption and the stock of durables in period t. I assume that the flow consumption generated by the stock of durables is proportional to the durable stock. x_t denotes the expenditures on durable investment in period t. a_t denotes the liquid savings in period t that earns an interest rate r. y_t denotes the household's income in period t. G_t and T are government spending and taxes. The difference between the two enters the budget constraint as a wealth component. When government spending increases in period t, either y_t or G_t or both increase, so a government spending shock represents a positive income or wealth shock. Finally, δ denotes the depreciation rate of the durable stock.

Utility maximization conditions imply that,

$$\frac{U_{d,t}}{U_{c,t}} = \frac{r+\delta}{1+r}$$

where $U_{c,t}$ and $U_{d,t}$ denote the marginal utility of nondurable and durable consumption. Let α be the expenditure share parameter in the Cobb-Douglas utility function for nondurable consumption, i.e., $U(c,d) = c^\alpha d^{1-\alpha}$. Then, the ratio between durable stock and nondurable consumption is constant, i.e.,

$$\frac{d_t}{c_t} = \frac{1+r}{r+\delta} \cdot \frac{1-\alpha}{\alpha} \equiv \kappa. \tag{2.11}$$

Further, the law of motion for durable stocks implies a relation between the change in the expenditures on durables and the change in nondurable consumption,

$$x_t - x_{t-1} = \kappa(c_t - c_{t-1}) + (1-\delta)\kappa(c_{t-1} - c_{t-2}).$$

Suppose that the economy is in steady state before time t, such that $c_{t-1} = c_{t-2}$. At time t, the government unexpectedly increases spending, and households adjust their consumption in response to this shock. Then the ratio between the response of expenditures on durables and nondurables, $(x_t - x_{t-1})/(c_t - c_{t-1})$, is κ. Based on the empirical estimates in Table 2.2,

$$\hat{\kappa} = \frac{0.65}{0.08} = 8.125.$$

The theoretical model implies that κ is determined by equation (3.3). I calibrate equation (3.3) using standard parameter values, and compare the model-implied responses with the empirical results. Specifically, I set $\alpha = 0.8$, consistent with the share of nondurable

expenditures in the NIPA data.[23] I set the annual real interest rate to be 0.02, consistent with the standard consumption literature in calibrating the real interest rate. I set the annual depreciation rate to 0.1, consistent with the BEA's depreciation rate for consumer durables. Finally, both the interest rate and the depreciate rate are converted to the quarterly rate, because the frequency of the CE data is quarterly. This implies $r = 0.005$ and $\delta = 0.025$. The calibrated model based on the consumer's optimization problem suggests that

$$\kappa = \frac{1+r}{r+\delta} \cdot \frac{1-\alpha}{\alpha} = 8.375,$$

which is close to the empirical counterpart. The intuition behind this result is as follows. When government spending creates labor demand and increases household income, consumers increase their stock of durables and the consumption of nondurables proportionately. Since the stock of durables is much larger than the consumption of nondurables in the data, a proportionate increase in both types of expenditures implies a much larger increase in the purchase of durables than nondurables. Although this model is a standard two-good consumer choice model with minimum restrictions on preferences. The calibrated model matches the empirical estimate of the ratio remarkably well.

2.8 Conclusion

This paper uses a novel dataset on federal government disaster-relief spending, combined with both household and state-level consumption, income and employment data, to answer the question of whether government spending can have a large effect on private consumption and income. My estimates show that the demand shock created by government disaster-relief spending stimulates private consumption and has an income multiplier of 1.8. This effect can be traced to the government's influence on the labor market. Based on the occupational information in the household survey data, I show that households who are most likely to work for disaster-relief related jobs have the largest consumption growth in states receiving disaster-relief spending from the federal government. When a state receives such spending, the industries in this state that provide most disaster-relief related jobs experience the largest employment growth. My analysis is supportive of the job-creation channel emphasized in Keynesian models of the effects of higher government spending. These findings are also likely to be relevant for other forms of government spending.

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[23]Alternatively, based on the CE data, durable expenditures also account for about 20 percent of total expenditures.

One challenge for this paper, and for future work, on disaster-relief spending is that the multiplier effect may be confounded with the direct impact of disasters, which can create either an upward or a downward estimation bias. I showed that controlling for the property losses incurred by households is one solution to this problem. In addition, I showed that the heterogeneous response across households cannot be all driven by the direct disaster impact, because in that case households living in the affected area, regardless of their occupation, income source and education, would be equally likely to encounter such a loss.

Finally, I stressed that my results have broader implications for the transmission of government spending shocks because the labor demand channel of government spending identified in this paper is also likely to affect other types of government spending. Teachers and educators, for example, are hired if the government spends on education. Engineers and scientists are hired when the government spends on defense and aerospace. Doctors and nurses are hired when the government spends on health and medical care. These examples illustrate that government spending tends to be industry specific, and that the job market channel documented in this paper should be in operation more generally. My analysis also suggests that policymakers interested in stimulating the economy should focus on the expenditures that support job creation.

Table 2.1: The response of total consumer expenditures, 1993-2014

	$\triangle c_{ist}$ (change in total expenditures)			
	(1)	(2)	(3)	(4)
$G_{s,t}$ (disaster spending per household)	0.84 (0.34)	0.70 (0.36)	0.73 (0.36)	0.72 (0.36)
$D_{s,t}$ (state property loss per household)		0.09 (0.10)		
$D_{s,t}^A$ (state property loss per household, adjusted)			0.12 (0.16)	0.12 (0.16)
Lagged disaster spending per household				-0.19 (0.28)
Household characteristics	Y	Y	Y	Y
Interview month dummies	Y	Y	Y	Y
State dummies	Y	Y	Y	Y
# Obs.	240,072	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.5). Standard errors are clustered at the household level. The change in total expenditures, disaster spending per household (and its lag), and state property loss per households (and the adjusted measure) are expressed in dollars. The coefficient in column (1), for example, represents the change in total expenditures per household resulted from one dollar of disaster relief spending per household. Household characteristics include the household head's age, gender, race, education, the family size and its change, the number of adults and its change, the household's income ranking in the previous year, and indicators of whether the household purchased car and/or homeowner insurance in the previous quarter. The adjusted loss measure $D_{s,t}^A$ is constructed by multiplying the loss $D_{s,t}$ by the share of the households in the state that neither purchased a car nor homeowner insurance in the previous quarter.

Table 2.2: The response by expenditure categories, 1993-2014

| | Food | Non-durables | Durables | Durables: | | | | | Vehicles: | |
				Equip-ment	Entertain-ment	Edu-cation	Vehicles	New	Used	Other
$G_{s,t}$	-0.01	0.09	0.65	0.03	0.03	0.04	0.55	0.50	0.04	0.01
	(0.05)	(0.18)	(0.29)	(0.04)	(0.05)	(0.05)	(0.27)	(0.22)	(0.12)	(0.01)
$D_{s,t}^{A}$	0.01	0.04	0.07	0.03	0.05	-0.03	0.01	-0.00	0.00	0.01
	(0.02)	(0.08)	(0.12)	(0.04)	(0.06)	(0.02)	(0.09)	(0.08)	(0.04)	(0.01)
# Obs.	240,072	240,072	240,072	240,072	240,072	240,072	240,072	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.5). Standard errors are clustered at the household level. All columns have the same right-hand variables as in column (3) of Table 2.1.

Table 2.3: The impact of disaster-relief spending by occupation, 1993-2014

	Total	Durables	New vehicles
$G_{s,t}$ (Not working)	0.48	0.57	0.46
	(0.54)	(0.45)	(0.30)
$G_{s,t} \times$ Grounds keeping	11.07	8.03	7.61
	(8.18)	(8.21)	(8.18)
$G_{s,t} \times$ Protective service	4.47	2.93	2.16
	(2.66)	(2.27)	(1.85)
$G_{s,t} \times$ Armed forces	4.10	-0.92	-1.59
	(2.33)	(1.81)	(1.45)
$G_{s,t} \times$ Repairer	2.17	1.21	1.81
	(2.64)	(2.40)	(2.22)
$G_{s,t} \times$ Technician	1.46	0.44	0.68
	(1.06)	(0.91)	(0.76)
$G_{s,t} \times$ Professional	1.09	0.57	0.18
	(0.99)	(0.78)	(0.61)
$G_{s,t} \times$ Construction	0.78	0.43	0.94
	(1.47)	(1.30)	(1.19)
$G_{s,t} \times$ Farming	0.69	2.80	0.00
	(2.62)	(2.52)	(1.21)
$G_{s,t} \times$ Helper	0.63	-0.12	-0.88
	(1.20)	(0.99)	(0.61)
$G_{s,t} \times$ Teacher	0.63	0.72	0.77
	(1.26)	(1.13)	(0.95)
$G_{s,t} \times$ Transportation operator	0.62	-0.70	0.33
	(1.51)	(1.38)	(0.90)
$G_{s,t} \times$ Business sales	0.44	0.20	-0.20
	(0.92)	(0.79)	(0.43)
$G_{s,t} \times$ Administrator	0.21	0.67	0.17
	(1.81)	(1.16)	(0.94)
$G_{s,t} \times$ Administrative	0.17	-0.24	-0.05
	(0.99)	(0.88)	(0.51)
$G_{s,t} \times$ Other service	-0.80	-0.98	-0.70
	(0.93)	(0.82)	(0.69)
$G_{s,t} \times$ Private household service	-1.18	-1.41	-0.42
	(1.45)	(0.94)	(0.31)
$G_{s,t} \times$ Retail sales	-1.89	-1.72	-1.33
	(1.25)	(1.00)	(0.53)
$G_{s,t} \times$ Operator,assembler	-2.02	-2.43	-1.29
	(4.23)	(4.26)	(4.09)
# Obs.	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.6). Standard errors are clustered at the household level. All columns have the same control variables as in column (3) of Table 2.1.

Table 2.4: The impact of disaster-relief spending by income source, 1993-2014

	Total	Durables	New vehicles
$G_{s,t}$ (Not Working)	0.48	0.57	0.47
	(0.54)	(0.45)	(0.30)
$G_{s,t}\times$ Self-employed	2.77	1.43	0.30
	(1.31)	(1.11)	(0.72)
$G_{s,t}\times$ Federal government	2.34	2.21	1.40
	(2.85)	(2.64)	(2.13)
$G_{s,t}\times$ Local government	0.88	0.53	0.18
	(0.99)	(0.82)	(0.62)
$G_{s,t}\times$ Private company	0.01	-0.11	0.02
	(0.72)	(0.58)	(0.43)
$G_{s,t}\times$ State government	0.01	-0.53	-0.35
	(1.48)	(1.14)	(0.97)
$G_{s,t}\times$ working without pay	-3.07	-0.53	0.36
	(3.57)	(2.50)	(2.14)
# Obs.	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.6). Standard errors are clustered at the household level. All columns have the same control variables as in column (3) of Table 2.1.

Table 2.5: The impact of disaster-relief spending by education, 1993-2014

	Total	Durables	New vehicles
$G_{s,t}$ (1-8 ys education)	0.72	-0.05	-0.08
	(0.40)	(0.18)	(0.11)
$G_{s,t} \times$ 9-12 yrs	-0.50	0.38	0.23
	(0.58)	(0.40)	(0.23)
$G_{s,t} \times$ High-school graduate	-0.92	-0.34	-0.17
	(0.62)	(0.45)	(0.34)
$G_{s,t} \times$ Occupational degree	1.45	1.86	1.45
	(0.87)	(0.73)	(0.54)
$G_{s,t} \times$ College degree	-0.73	0.61	0.48
	(1.02)	(0.57)	(0.43)
$G_{s,t} \times$ Graduate school	0.19	0.85	0.86
	(0.83)	(0.59)	(0.51)
$G_{s,t} \times$ Never attend school	0.60	0.04	0.30
	(1.44)	(0.71)	(0.23)
# Obs.	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.6). Standard errors are clustered at the household level. All columns have the same control variables as in column (3) of Table 2.1.

Table 2.6: The impact of disaster-relief spending during economic slack, 1993-2014

	Total	Durables	New vehicles
$G_{s,t}$	0.73	0.65	0.50
	(0.36)	(0.29)	(0.22)
$G_{s,t} \times \triangle U_{s,t}$	-1.37	-1.02	-0.48
	(0.69)	(0.57)	(0.42)
$\triangle U_{s,t}$	-28.24	-37.81	-21.32
	(68.58)	(55.74)	(39.10)
# Obs.	240,072	240,072	240,072

Notes: Pooled OLS estimates based on model (2.7). Standard errors are clustered at the household level. All columns have the same control variables as in column (3) of Table 2.1. $\triangle U_{s,t}$ denotes the change in the unemployment rate from period $t-1$ to t in state s.

Table 2.7: Consumption responses based on state-level data, 1997-2014

	PCE	PCE private	Non-durables	Services	Durables
Disaster spending	0.62	0.78	0.25	0.33	0.20
	(0.39)	(0.36)	(0.08)	(0.23)	(0.11)
Property loss	-0.05	-0.07	0.01	-0.07	-0.00
	(0.09)	(0.09)	(0.02)	(0.05)	(0.03)
Year dummies	Y	Y	Y	Y	Y
State dummies	Y	Y	Y	Y	Y
# Obs.	816	816	816	816	816
Adjusted R^2	0.749	0.748	0.712	0.716	0.730

Notes: Pooled OLS estimates based on model (2.8). Standard errors are clustered at the state level.

Table 2.8: Income responses based on state-level data, 1997-2014

	GDP	Personal income	Personal income net of transfer	Personal income net of farm inc.
Disaster spending	2.18	1.80	1.80	1.88
	(0.62)	(0.84)	(0.83)	(0.83)
Property loss	-0.52	-0.20	-0.18	-0.16
	(0.25)	(0.15)	(0.15)	(0.17)
Year dummies	Y	Y	Y	Y
State dummies	Y	Y	Y	Y
# Obs.	816	816	816	816
Adjusted R^2	0.298	0.603	0.680	0.666

Notes: Pooled OLS estimates based on model (3.1). Standard errors are clustered at the state level.

Table 2.9: Employment responses based on state-level data, 1997-2014

	Employment change in				
	Total Nonfarm	Goods	Services	Construction	Waste management, remediation services
Disaster spending (million)	7.92 (4.27)	4.58 (2.51)	3.34 (2.00)	3.01 (1.23)	1.56 (0.53)
Year dummies	Y	Y	Y	Y	Y
State dummies	Y	Y	Y	Y	Y
# Obs.	816	816	816	704	784
Adjusted R^2	0.758	0.724	0.688	0.571	0.469

Notes: Pooled OLS estimates based on model (3.9). Standard errors are clustered at the state level.

The Stafford Act Procedure for Declaring an Emergency or a Major Disaster
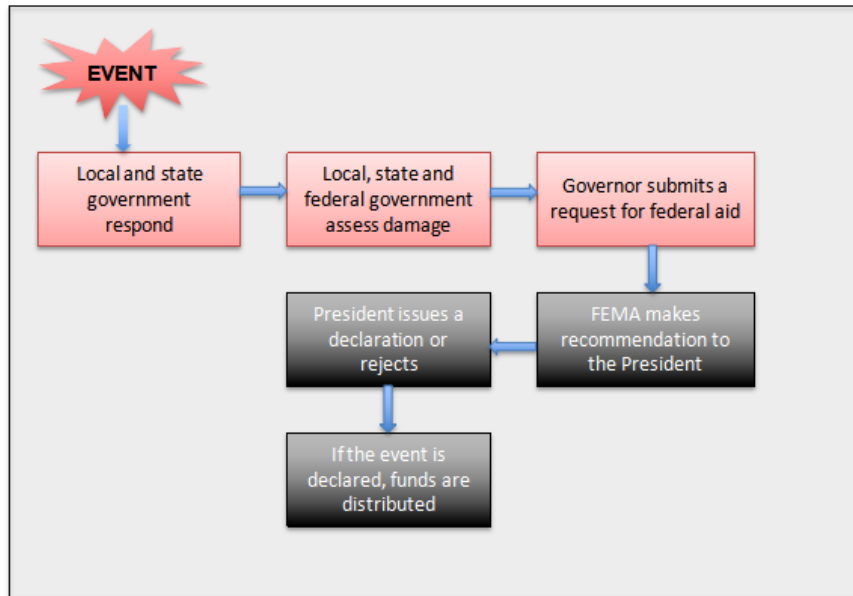
Source: *FEMA's Disaster Relief Fund: Overview and Selected Issues (2014)* by Bruce Lindsay, Congressional Research Service.

Figure 2.1: Federal disaster declaration procedure

Notes: This figure illustrates the disaster declaration procedure used by FEMA specified in the Stafford Act.
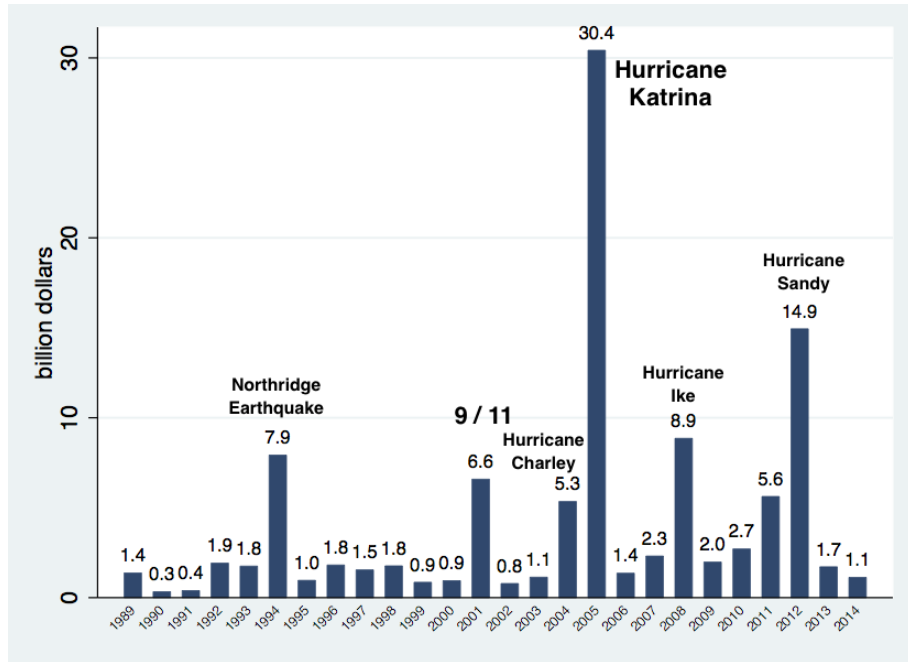
Figure 2.2: Disaster-relief funds obligated by FEMA (billion dollars), 1989-2014

Notes: Author's computations based on FEMA data from www.fema.govdata-feeds.
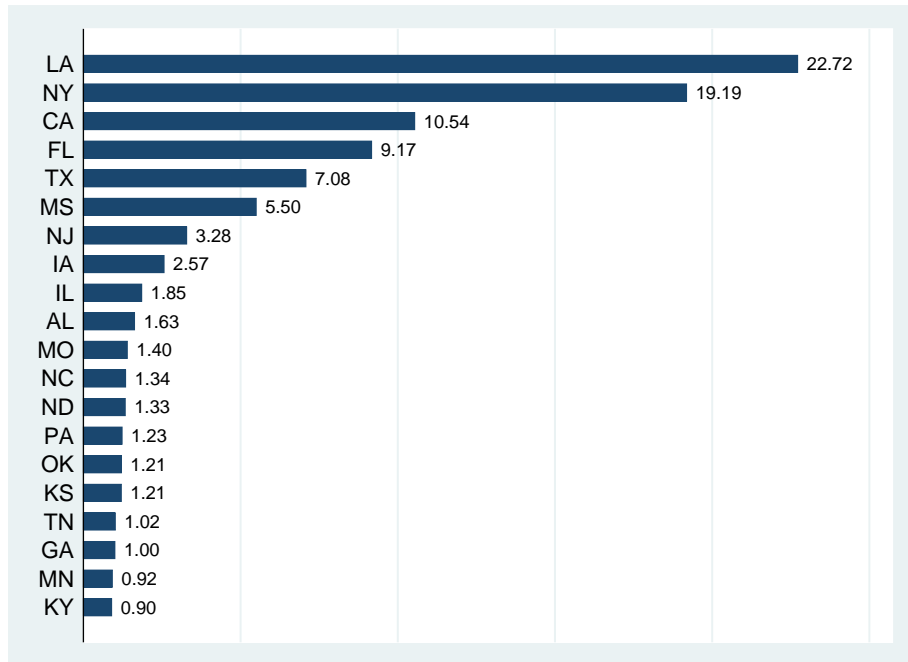
Figure 2.3: Top 20 state recipients of FEMA funds (billion dollars), 1989-2014

Notes: See Figure 2.2
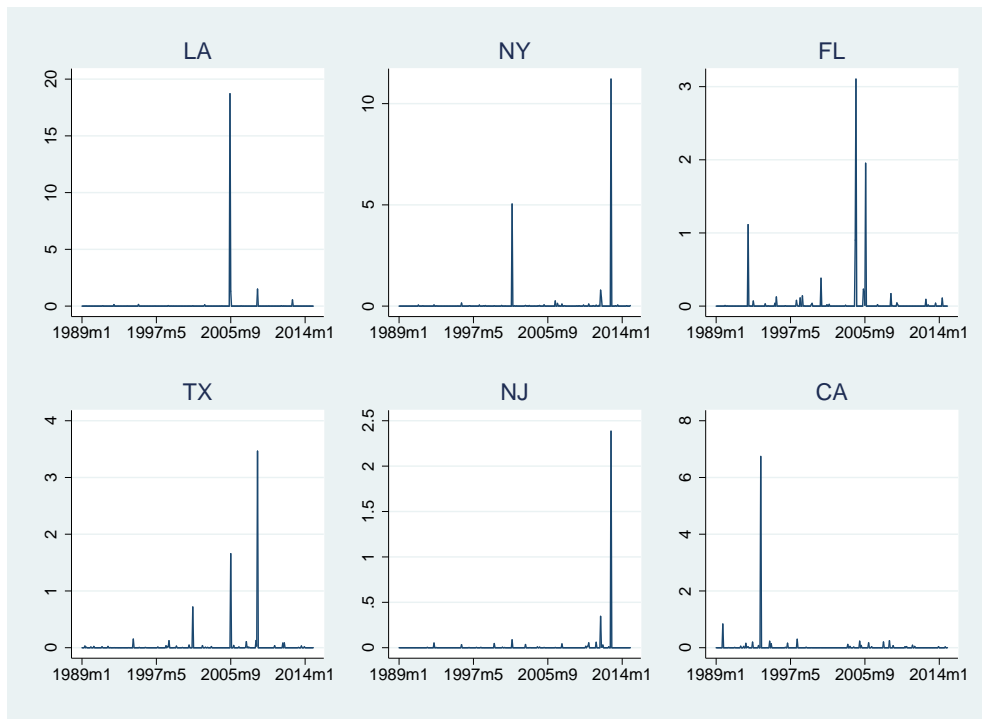
Figure 2.4: Within-state variation by month in disaster-relief funds received from FEMA (billion dollars)

Notes: See Figure 2.2.
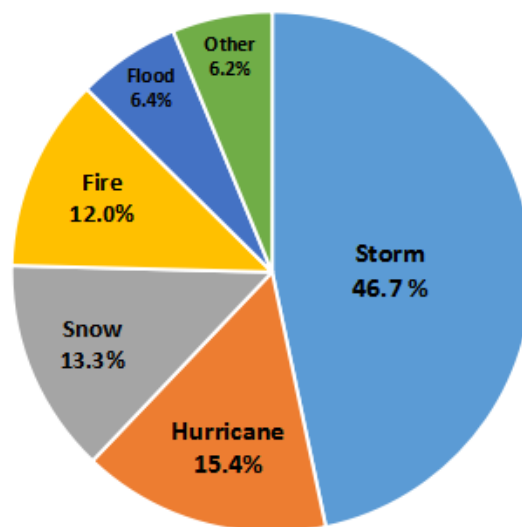
Figure 2.5: Categories of FEMA declared disasters, 1989-2014

Notes: This figure illustrates the major disaster categories funded by FEMA. The percentage is computed by counting the number of events in the corresponding category divided by the total number of funded disasters. Between 1989 and 2014, there were 1,824 funded disasters, according to FEMA's records.
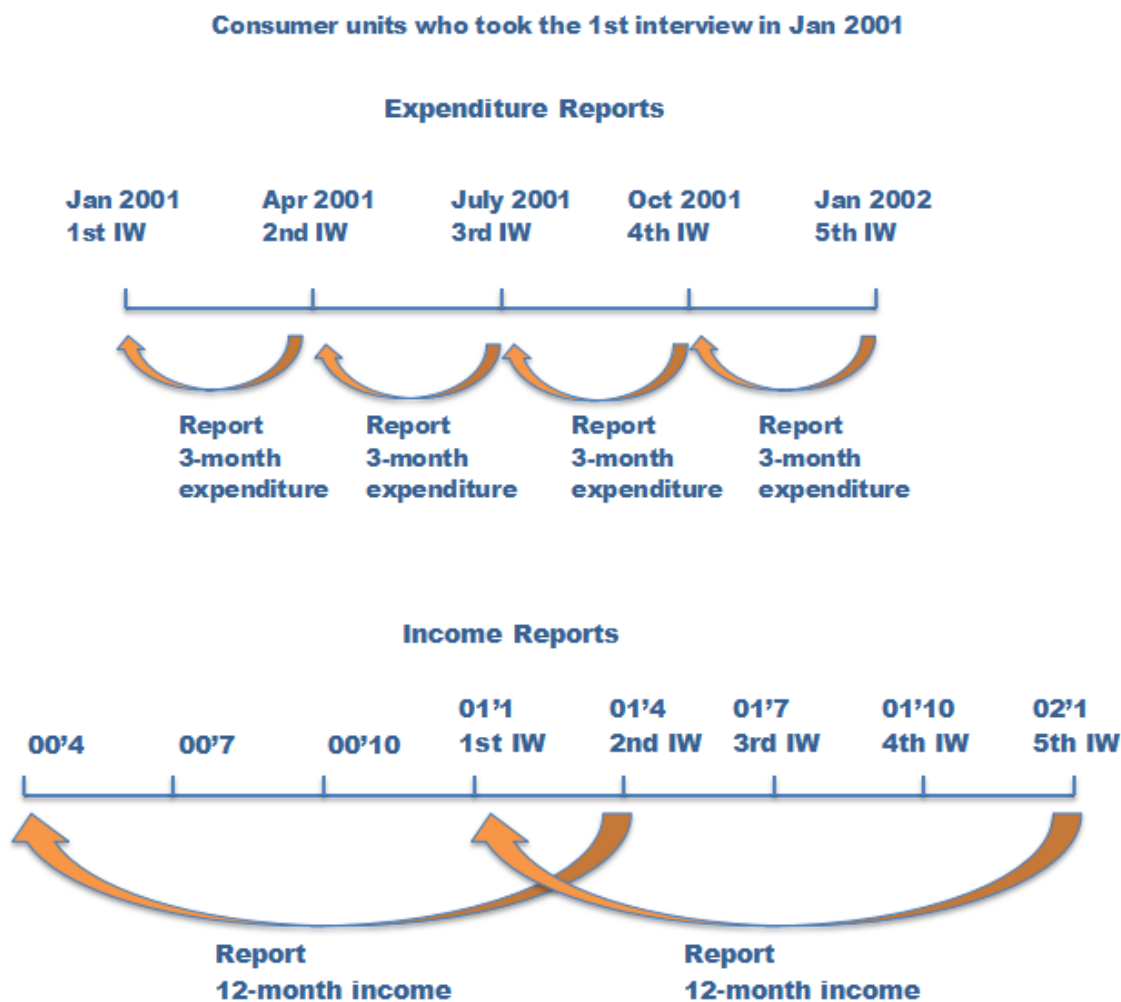
Figure 2.6: Consumer Expenditure Survey report structure

Notes: This figure illustrates the data report structure of a consumer unit that receives the first interview in January, 2001. There are four follow-up interviews in April 2001, July 2001, October 2001 and January 2002. In each interview, expenditures are reported for the past 3 month. Income is reported only in the second and the fifth interview, and is reported for the past 12 months.

CHAPTER 3

A Quantitative Evaluation of the Housing Provident Fund Program in China

3.1 Introduction

Governments around the world take measures to support homeownership. These actions are driven by the belief that housing, for most households, is both an important investment asset and a necessary consumption good, and that homeownership promotes social and economic stability. The U.S. government, for example, has fostered homeownership by encouraging subprime lending and expanding secondary mortgage markets (see, e.g., Mian and Sufi (2009) and Gabriel and Rosenthal (2010)). Arguably as a result, the U.S. homeownership rate reached 70% in 2004, compared to 60% in 1960 and 40% in 1940. Since the mortgage crisis of 2008, however, this rate has dropped back to 65%. Many Asian governments, in contrast, have adopted more centralized, mandatory savings plans that aim to fund households' housing needs. The Housing Provident Fund (HPF) in China is one such an example. Table 3.1 provides examples of similar programs in other countries.

The HPF was first enacted in 1999 and has been applied to an increasing number of regions of the country since then.[1] The policies stipulated by the HPF apply to all urban workers, regardless of the type of the enterprise they work for. There are two key features of this program. First, it is a mandatory savings scheme intended to fund housing purchases. Specifically, the government requires each worker to deposit a mandatory fraction of his or her salary to the program until the worker purchases his or her first house, at which point the government refunds the worker's past deposits. After the worker purchases the first house, the HPF still collects a fraction of the worker's salary every month, but refunds this amount to the worker usually within the same month. If the worker never purchases a house during his or her working life, the HPF returns all past deposits to the worker at

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[1]For further details on the HPF and a review of the history of related Chinese housing policies, see Xu (2016).

the time he or she retires. Second, the program provides below-market rate mortgages to participants. The HPF is the largest public housing program in China, both in terms of the number of workers enrolled and of the funds deposited and distributed. According to the annual report published by the Ministry of Housing and Urban-Rural Development in China, in 2015, 124 million workers enrolled in the HPF (16% of the labor force), 1.5 trillion Yuan (2% of GDP) were deposited in the program, and 1.1 trillion Yuan were lent out for home purchases and building.

There has been much interest in the question of how effective this program has been at stimulating homeownership (see, e.g., Logan et al. (1999), Li (2000), Fu et al. (2000), Huang and Clark (2002), Buttimer et al. (2004), Meng et al. (2005), Yeung and Howes (2006), Xu (2016), and Tang and Coulson (2017)). Empirically evaluating the success of this program is not easy. There are several challenges. For example, at the micro level, workers may select when to join the program. If this decision depends on unobserved characteristics, regression estimates suffer from selection bias. Alternatively, one may exploit regional variation in the timing of the implementation of this program. To the extent that the adoption of this program is anticipated by households, however, the causal effect will not be identified. Finally, at the national level, the length of time for which these policies have been in effect is too short to estimate the impact of the program, even if a credible counterfactual could be constructed.

Given these empirical challenges, the current paper uses a calibrated life-cycle model to quantitatively evaluate the expected impact of the HPF program. The use of quantitative theory also helps understand the mechanisms by which these polices affect the housing market. I focus on the effect of the program on two outcome variables: the rate of homeownership and the average home size. The baseline model captures the consumption and savings behavior of Chinese households over their life cycle. Households can choose both the timing and the size of their home purchase. Within the same generation, households are heterogeneous in that each house purchase is associated with a randomly drawn transaction cost. As a result, homeownership and average home size vary over the life cycle and across households. I calibrate the model based on household survey data from the Chinese Household Income Project Series. The model produces a rate of homeownership that is increasing with age, and a roughly flat path of the avergage home size over the life cycle.

I then incorporate the two key features of the HPF program into this baseline model. First, the mandatory-savings feature is captured by a parameter that represents the fraction of income to be deposited into the program. Second, the mortgage subsidies are captured by the below-market mortgage rate. I set these parameters according to the values

implemented by the HPF program in China. Finally, I compare the life-cycle path of the rate of homeownership and of the average home size with the corresponding paths in the baseline model.

My analysis shows that a housing program with these features is expected to increase the rate of homeownership by 4 percentage points in steady state, which is equivalent to a 10% increase in the homeownership rate relative to the baseline model. This increase is mainly due to the fact that many young households, who would otherwise buy a house later in life or who would simply choose never to buy a house, under this program choose to become homeowners. In addition, the average home size increases by 21% relative to the baseline model. This effect is mainly driven by middle-aged and old homebuyers.

To understand these results, I conduct two additional policy experiments. First, I consider a housing program that requires mandatory savings, but that does not offer mortgages at below-market rates. Second, I consider a program that offers subsidized mortgages, but that does not require mandatory savings. I show that each of these alternative programs on its own raises the homeownership rate almost as much as both programs combined. The main benefit of combining both programs is an increase in the average house size.

The model provides some interesting insights into how these policies affect economic outcomes. For example, the mandatory savings program forcibly reallocates a fraction of the income of young households to later in their life, making it harder for young people, who are already liquidity constrained, to smooth consumption. Hence, many households choose to become a homeowner earlier in life to avoid additional forced savings. In contrast, the mortgages offered at a below-market rate create a wealth effect that allows households to borrow at a lower cost. This effect drives more households to purchase a house earlier in their life and to purchase a larger house.

The remainder of the paper is organized as follows. Section 3.2 describes the baseline model and discusses how to incorporate the key features of the HPF program into the baseline model. Section 3.3 outlines the model calibration. Section 3.4 presents the results from a series of policy experiments. Section 3.5 extends the model to incorporate employer contributions. Section 3.6 concludes.

3.2 Model

The baseline partial equilibrium life-cycle model is intended to capture households' decisions about non-housing consumption (henceforth referred to as consumption), the

timing of purchasing one's first home, and the size of this home purchase.[2] The model has two important features. First, following Leahy and Zeira (2005), I make the simplifying assumption that households purchase a house, if at all, only once in their lives. Second, a house purchase is associated with a randomly drawn transaction cost. This assumption creates heterogeneity across households within the same generation. I then introduce the two key features of the HPF program, and embed these features into the baseline model.

3.2.1 Baseline Model

Time is discrete. The economy is populated with overlapping generations of households whose income and wealth differ across the life cycle. In each period, a mass of households is born and lives for J periods. In the first J_y periods of life, households work and earn labor income. In the remaining $J - J_y$ periods, households retire and receive retirement income.

Households start their life without a house. In each period, households make decisions about consumption, about whether to become a homeowner if they are not already, about the size of the home they decide to buy, and about their savings for the next period. At the end of their life, households leave their total wealth as a bequest, consisting of savings and the value of their house.

A household maximizes expected lifetime utility,

$$E_0\left\{\sum_{j=0}^{J-1}\beta^j\left[u(c_j)+v(h_j)\right]+\beta^J\Phi(w_J)\right\}$$

where c and h denote consumption and the home size, respectively. I assume that the flow service generated by the house is proportional to the home size. The second term inside the expectation operator represents the discounted utility from leaving a bequest, specified by the bequest function Φ, the functional form of which is discussed in Section 3.3. w_J denotes the total wealth at the end of the household's life.

The household problem has a recursive form. The value at the end of the household's life, V_J, is given by the bequest function,

$$V_J(a,h) = \Phi\left((1+r)a+ph\right)$$

where a denotes savings, p denotes the house price, and h denotes the home size. For

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[2]The partial equilibrium consumption-choice framework, unlike a standard general equilibrium model of the housing market (see, e.g., Iacoviello and Neri (2010)), has the advantage of modeling more complicated household decisions, such as discrete purchases and heterogeneous household behavior (see, e.g., Ortalo-Magne and Rady (2006), Yang (2009), Iacoviello and Pavan (2013), and Berger et al. (2015)).

lifetime period $j = 0, ..., J-1$, the value V_j depends on whether the household owns a house at the beginning of the period. If the household owns a house of size h at the beginning of the period, the value is given by

$$V_j(a,h) = \max_{c,a'} \quad u(c) + v(h) + \beta V_{j+1}(a',h)$$
$$s.t. \quad c + a' = y + (1+r)a$$
$$-a' \leq \gamma p h.$$

The first constraint is the budget constraint, where y denotes income and r denotes the interest rate. The second constraint is the collateral constraint. If the household borrows, the borrowing amount cannot exceed a fraction γ of the home value.

If the household does not own a house at the beginning of the period, V_j is the maximum of the value of purchasing a home, V_j^P, and of not purchasing a home, V_j^N, i.e.,

$$V_j(a,f) = \max\left\{V_j^P(a,f), V_j^N(a)\right\}.$$

The value of purchasing a home is

$$V_j^P(a,f) = \max_{c,a',h'>0} \quad u(c) + \beta V_{j+1}(a',h')$$
$$s.t. \quad c + a' + ph' = y + (1+r)a - f$$
$$-a' \leq \gamma p h'$$

where f is a randomly drawn transaction cost from a continuous distribution F. The value of not purchasing a home is

$$V_j^N(a) = \max_{c,a'} \quad u(c) + \beta E\left[V_{j+1}(a',f')\right]$$
$$s.t. \quad c + a' = y + (1+r)a$$
$$a' \geq 0$$

where $E\left[V_{j+1}(a',f')\right] = \int_{-\infty}^{\infty} V_{j+1}(a',f')dF(f')$. The second constraint is the liquidity constraint, which requires liquid savings to be non-negative. The presence of the collateral constraint and the liquidity constraint jointly imply that any positive borrowing amount must be collateralized by a house.

3.2.2 Modeling Mandatory Savings

One important feature of the HPF program is a mandatory savings requirement for workers who are not homeowners. Specifically, the government requires each worker to deposit a mandatory fraction of his or her salary to the HPF until the worker purchases his or her first house, at which point the government refunds the worker for all past deposits. After the worker purchases the first house, the HPF still collects a fraction of the worker's salary every month, but refunds this amount to the worker usually within the same month. This is equivalent to not requiring any deposit to the HPF after the worker purchases the first house. Therefore, when modeling the mandatory savings requirement, I assume that existing homeowners are not affected by this requirement.

The mandatory-savings requirement affects the budget constraint of workers who choose not to purchase a house. After subtracting a fraction of their income, for $j = 0, ..., Jy - 1$,

$$V_j^N(a) = \max_{c,a'} \quad u(c) + \beta E\left[V_{j+1}(a', f')\right]$$

$$s.t. \quad c + a' = (1 - \theta)y + (1 + r)a$$

$$a' \geq 0$$

where θ is the fraction of a worker's income taken away by the program.

The HPF refunds the worker for all past deposits with interest if the worker purchases a house. The value of purchasing a house at age $j = 1, ..., Jy$ becomes

$$V_j^P(a, f) = \max_{c,a',h'>0} \quad u(c) + \beta V_{j+1}(a', h')$$

$$s.t. \quad c + a' + ph' = y + (1 + r)a - f + \theta \sum_{k=0}^{j-1} y_k(1 + r)^{j-k}$$

$$-a' \leq \gamma ph'.$$

Finally, if the worker never purchases a house during his or her working life, the HPF returns all past deposits to the worker at the time he or she retires. This implies that the budget constraint for a non-homeowner at the retirement age has an extra income term, $\theta \sum_{k=0}^{Jy-1} y_k(1 + r)^{Jy-k}$. Since the mandatory savings requirement does not apply to any retired workers, the household problem during the retirement is the same as in the baseline model.

3.2.3 Modeling Below-Market Rate Mortgages

In an effort to make housing more affordable, the HPF provides below-market rate mortgages. According to the People's Bank of China, the historical spread between the long-term market mortgage rate and the HPF's lending rate is about 2 percentage points. In modeling the mortgages provided by the HPF, I assume that households have two financial assets: liquid savings that earns a market interest rate, and a mortgage debt that is repaid at the rate specified by the HPF. I consider an interest-only repayment schedule that requires interest to be paid every period, but the principal to be paid when the mortgage contract terminates.[3]

Allowing two financial assets adds an additional state variable to the model, which greatly increases the computational cost of solving the model. The value V_J at the end of the household's life becomes

$$V_J(a,h,b) = \Phi\big((1+r)a + ph - (1+r^b)b\big)$$

where a denotes liquid savings, r denotes the market interest rate, b denotes the amount of mortgage debt, and r^b denotes the mortgage rate set by the HPF.

For lifetime period $j = 0,...,J-1$, the value V_j depends on whether the household owns a house and a mortgage at the beginning of the period,

$$V_j = \begin{cases} V_j(a,h,b), & if \quad h > 0 \\ V_j(a,f), & if \quad h = 0. \end{cases}$$

where

$$V_j(a,h,b) = \max_{c,a'} \quad u(c) + v(h) + \beta V_{j+1}(a',h,b')$$
$$s.t. \quad c + a' = y + (1+r)a - M$$
$$a' \geq 0$$
$$b' = (1+r^b)b - M$$

where M is the periodic interest repayment. b' is the mortgage debt at the beginning of the next period. The liquidity constraint applies to liquid savings.

If the household does not own a house at the beginning of the period, V_j is the maximum between the value of purchasing a house V_j^P and not purchasing V_j^N. V_j^N is the same as in

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[3]I also considered an alternative, fully amortized repayment schedule that consists of equal repayments in all periods. The results are quantitatively similar.

the baseline model, because a lower mortgage rate would not affect households who choose not to buy a home. V_j^P becomes

$$V_j^P(a, f) = \max_{c, a', h' > 0, b' \geq 0} u(c) + \beta V_{j+1}(a', h', b')$$
$$s.t. \quad c + a' + ph' = y + (1 + r)a - f + b'$$
$$a' \geq 0$$
$$b' \leq \gamma ph'.$$

Given this analysis, it is straightforward to combine Sections 3.2.2 and 3.2.3 to model the two program features simultaneously.

3.3 Calibration

In order to quantify the impact of the HPF program, the model parameters are calibrated. A summary of the parameter values can be found in Table 3.2. Age is indexed by $j = 0, ..., J - 1$. The model frequency is five-year intervals. Households start their life at age 20, work for 40 years until age 60, and then live for 20 years in retirement, so $J = 12$ and $Jy = 8$. Households do not have initial liquid savings, i.e., $a_0 = 0$.

The discount factor is set to $\beta = 0.93$. The utility function is,

$$u(c) + v(h) = \begin{cases} \ln c + s \ln h, & if \quad h > 0, \\ \ln c & if \quad h = 0. \end{cases}$$

where s denotes the utility weight on housing services. I set $s = 0.25$, so that the expenditures on housing account for 20% of total consumer expenditures, consistent with household survey data from the Chinese Household Income Project Series for 2002.[4]

The bequest function is

$$\Phi(w) = \eta \ln(w)$$

where $w \equiv (1 + r)a + ph - (1 + r^b)b$ denotes the total wealth. η is the bequest parameter. I set $\eta = 1$.

I use the Chinese Household Income Project Series data for 2002 to calibrate household

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[4]The Chinese Household Income Project Series (CHIPS) are intended to measure the distribution of personal income in both rural and urban areas of China. These survey data were collected in 1988, 1995 and 2002. Individual respondents reported their demographic characteristics, income, employment, and expenditures. I obtain the 2002 CHIPS data from the ICPSR at the University of Michigan.

income by age group. The survey provides the household head income between 1998 and 2002. I average the head income across these years, and compute the mean for each age group. I normalize the income of age group 26-30 to 1. Figure 3.1 shows the age distribution of income.

I normalize the house price to $p = 1$. The mandatory fraction of income to be deposited into the program is set as $\theta = 0.15$, consistent with the average of the workers' contribution rate across cities in China from 1999 to 2015. The market savings rate is set at $r = 0.05$, consistent with the deposit interest rate in China. In all simulations, the HPF program creates an interest rate spread of 2 percent, i.e., $r^b = 0.03$. The transaction cost is assumed to be normally distributed with the mean and variance chosen to match the distribution of homeownership rate by age group.

3.4   Policy Experiments

In this section, I evaluate the impact of the HPF program on the homeownership rate and on the average home size in steady state. This helps control for transition dynamics as the program is introduced. I compute the optimal life-cycle choices in steady state by simulating the life-cycle profiles of 4,000 households. I show that the program meets the government's objective of enhancing homeownership. The expected increase is 4 percentage points. The HPF also raises the average home size by 21%. Since the program has two distinct features, each of which may affect household decisions differently, I also investigate the impact of these two features separately. The results are summarized in Table 3.3. I conclude that each feature alone can enhance homeownership and the home size almost as much as the two features combined. The main benefit of combining both features is an increase in the average house size. I also examine how sensitive the rate of homeownership and the average home size are to changes in the key policy parameters.

3.4.1   The Impact of HPF

Figure 3.2 shows the life-cycle profile of four key variables in the baseline model (solid lines) and under the HPF program (dotted lines). These variables include the purchase rate (the fraction of homebuyers), the homeownership rate (the fraction of homeowners), the average purchase size of homebuyers, and the average home size of all homeowners. In the baseline model, the purchase rate, shown in the upper left panel, peaks at age 30 to 35 and then gradually declines. Since for each age group there is always a fraction of households becoming new homeowners, the homeownership rate, shown in the upper right panel, is

monotonically increasing with age and is concave after age 35. The purchase size in the lower left panel shows a weak hump during age 35 to 70. After age 70, the purchase size declines, because the life horizon shortens. Simply put, old purchasers do not need a large home. The average home size, shown in the lower right panel, is roughly flat across age. This means that in the baseline model households within the same generation do not differ much in the size of the home they purchased, but that they do differ in the timing of their purchases.

Under the HPF program, a substantial fraction of households purchases their homes at age 25 to 30, earlier than in the baseline model. In addition, households between age 70-75 increase their purchases. For all other age groups, the program does not change much the purchase rate. This implies that there are some households who otherwise would not purchase a house, but choose to buy one under this program. The average homeownership rate across all age groups increases by 4 percentage points relative to the baseline model, as shown in Table 3.3. The average purchase size increases in all age groups under the HPF program, especially after age 30. This implies that the average home size increases in all ages. Overall, the average home size across all age groups increases by 21% relative to the baseline model.

To understand these results, I conduct two additional policy experiments in the remainder of this section. First, I consider a housing program that requires mandatory savings, but that does not offer mortgages at below-market rates. Second, I consider a program that offers below-market rate mortgages, but that does not require mandatory savings.

3.4.2 The Effect of the Mandatory-Savings Policy in Isolation

Figure 3.3 shows for different age groups the home purchase rate and the average size of new homes purchased, when the government introduces a housing program that only has a mandatory savings feature as described in Section 3.2.2. As shown in the left panel, the mandatory savings policy pushes forward the timing of purchasing a home, especially for young households. It also increases the homeownership rate in all age groups. The intuition is that the mandatory savings program forcibly reallocates a fraction of income of young households to later in their life, making it harder for young people, who are already liquidity constrained, to smooth consumption. Hence, many households choose to become a homeowner earlier in life to avoid these forced savings. Since more young households choose to buy a home at the time when they do not have much income, they choose a smaller home. Those who purchase a house in a later stage of life get refunded for the past

mandatory deposits, allowing them to afford a larger home, as shown in the right panel.

The mandatory savings policy also affects household wealth and consumption. As shown in Figure 3.4, mandatory deposits during the working life reduce household liquid wealth, and create a jump in wealth at the retirement age when non-homeowners get a large refund from all previous mandatory savings. This implies that the consumption path is less smooth, and also exhibits a major jump at the retirement age.

3.4.3   The Effect of Below-Market Mortgage Rates in Isolation

Figure 3.5 shows the home purchase rate and the average size of new homes purchased by age group when the government introduces a housing program that provides below-market rate mortgages as described in Section 3.2.3. This policy lowers the borrowing cost and hence creates a wealth effect for all homeowners. Many young households choose to purchase a house earlier in their life at age 30, rather than age 35, as housing becomes more affordable in the early stage of life. This policy also drives some old households aged 70 to 75, who otherwise would not become a homeowner, to purchase a house. This directly explains the increase in the home purchase rate at age 75 under the HPF program, as shown in Figure 3.2. The policy increases overall home purchase size, especially of middle-aged and old homebuyers, again due to the wealth effect.

The wealth effect of this policy can be illustrated by plotting the average wealth over the life cycle. Figure 3.6 shows that average wealth increases at all ages. Because of this wealth effect, average consumption beyond age 45 is higher than in the baseline economy. Consumption below age 45 is lower, because many households in that age group choose to purchase a house in response to this policy.

3.4.4   Sensitivity Analysis

There are two key parameters in the model that capture the features of the HPF program: workers' contributions to the program, expressed as a fraction θ of income, and the mortgage rate provided by the program, r^b (or equivalently, the interest rate spread, $r - r^b$). I now examine how sensitive the homeownership rate and the average home size are to changes in these parameters. Figure 3.7 shows the homeownership rate and the home size normalized relative to the baseline model as a function of θ, assuming a mortgage rate of 2 percent below the market rate. For low θ, the homeownership rate is not sensitive to θ. Increasing θ only increases the average home size. For θ greater than 0.15, increasing θ further raises both the homeownership rate and the average home size. Figure 3.8 shows the results of a similar exercise with θ fixed at 0.15 and different values of the mortgage rate.

As long as the mortgage rate is only slightly below the market rate, the homeownership rate does not change much. As the mortgage spread widens beyond about 2 percent, both variables increase.

3.5 The Role of the Employer Contribution

Another feature of the HPF program is that the employer of a program participant is required by the government to contribute to the participant's HPF savings. Both the worker's deposits and the employer's contributions are refunded to the worker with interest when the worker purchases a house or retires, whichever is earlier. How much an employer contributes, however, is chosen by the employer, and varies according to local regulations and the employer's profit condition. The HPF program requires that the employer should contribute 5-20% of the worker's income, and that the employer's contribution should not exceed the worker's deposit. In addition, unprofitable firms may lower their contributions, or may temporarily suspend them.

To understand how this additional feature affects homeownership and the average home size, I first consider a model without the below-market mortgage rates. I consider a housing program that requires a participant to deposit 15% of his or her income and requires the employer to match x% of the worker's deposit, where $0 \leq x \leq 100$. For example, $x = 0$ represents the program in section 3.2.2, and $x = 100$ means that the employer matches the worker's contribution dollar by dollar.

Figure 3.9 shows the results for this exercise. When x is high, households tend to postpone their home purchase. This is especially true for young households. The intuition is that the longer a worker contributes to the program, the more additional contributions will be made by his or her employer. As a result, when x is high, many households delay their home purchase until retirement. In contrast, when x is low, the employer contribution has almost no incremental effect on the homeownership rate. However, it does increase the average size of new homes.

Next, I reintroduce the below-market mortgage rate feature and show that the effect on the average homeownership rate and the average home size are robust to the inclusion of employer contributions. Table 3.4 summarizes the homeownership rate and the average home size for different x, where $x = 0$ represents the HPF program discussed in section 3.4.1. Employer contributions increase the homeownership rate slightly once x approaches 80. Likewise, the average home size rises slightly once x increases beyond above 50. Overall, however, the results in section 3.4.1 are robust to the inclusion of employer contributions.

One can also break down these results by age. Similar to Figure 3.9, Figure 3.10 shows the effect of employer contributions by age. When x is low, employer contributions have almost no incremental effect on the purchase rate. When x is high, on the one hand, young households postpone their purchase decisions, and on the other hand, many old households, who have accumulated enough savings both from their own deposits and from employer contributions, choose to become homeowners. The average size of new homes also increases with the employer contribution rate.

3.6   Conclusion

There has been much interest in the question of how the HPF has affected homeownership in China. This question is of interest not only to Chinese authorities but to policymakers more broadly, because similar policies have been implemented in a range of countries. Addressing this question empirically is not straightforward because of selection bias, because of anticipation effects, and because of the short duration of this program to date.

An alternative approach to quantifying the expected effects of this program is the use of quantitative theory. Existing theoretical studies of this question have relied on representative-agent models (see., e.g., Buttimer et al. (2004) and Tang and Coulson (2017)). Such models are not well-suited for studying the effect of these policies, because in representative-agent models either everyone or no one buys a house. The current paper introduces a life-cycle model with heterogeneous agents that allows agents' purchases of homes to depend on their age and unobserved characteristics. This model allowed me to quantify the increase in homeownership one would expect in response to this program. I showed that the HPF program is expected to increase the rate of homeownership by 4 percentage points in steady state. It also increases the average size of homes. This result is robust to allowing employers to match the workers' contributions in part or in full.

One advantage of addressing this question based on a theoretical model is a better understanding of the mechanisms by which these policies affect economic outcomes. I find that the mandatory savings program affects home purchases primarily by making it hard for young people, who are already liquidity constrained, to smooth consumption. Hence, many of these households choose to become a homeowner earlier in life to avoid additional forced savings. The HPF program accounts for as much as a 7 percentage point increase in the purchase rates among young households with little additional effect on households of older ages.

Regardless of how long households are forced to save, the program provides access to subsidized mortgages intended to make home more affordable. Households' ability to take

advantage of these rates depends on unobservable characteristics. In the calibrated model, the fraction of participating households who are unable to buy a house by the end of their life time is about 30%. I show that the incremental contribution of subsidized mortgage rates to the rate of homeownership is minor. However, subsidized mortgage rates may serve as an effective substitute for mandatory savings plans.

Although the model presented in this paper is more realistic than previous theoretical analysis of Chinese housing policies, my analysis in this paper is only a first step. A more detailed analysis of the effects of Chinese housing policies would have to take account of changes in house prices and monetary policies, for example. Incorporating these features into the life-cycle framework is nontrivial and left for future research.

Table 3.1: Government savings programs intended to foster homeownership

Country	Program	Mandatory	Contribution as a fraction of income (%)	Purpose
China	HPF	Yes	5 - 20	Housing, retirement
Singapore	CPF	Yes	5 - 20	Housing, education medical care, retirement
India	EPF	No	12	Housing, education medical care, retirement marriage
Malaysia	EPF	Yes	8 - 11	Housing, retirement

Source: Information complied from the official websites of the various programs.
China's HPF (Ministry of Housing and Urban-Rural Development of China):
www.mohurd.gov.cn/zfgjjjg/index.html.
Singapore's CPF (CPF Board): www.cpf.gov.sg/members.
India's EPF (EPF Organisation): www.epfindia.com/site_en/.
Malaysia's EPF: www.kwsp.gov.my/portal/en/web/kwsp/home.

Table 3.2: Calibration

Parameter		Value
Demographics		
J	Number of age groups	12
J_y	Number of working periods	8
Preferences		
β	Discount factor	0.93
s	Utility weight on housing	0.25
η	Utility weight on bequest	1
Transaction cost		
μ_f	Mean of the distribution	1.5
σ_f	Std. dev. of the distribution	1
Aggregate variables		
p	House price	1
r	Market savings rate	0.05
Policy parameters		
θ	Fraction of income deposited	0.15
r^b	Discounted mortgage rate	0.03

Notes: This table shows calibrated parameters. See Section 3.3 for method description.

Table 3.3: Summary of steady-state results

	Baseline	HPF program	Mandatory-savings feature only	Low-rate-mortgage feature only
Homeownership rate	40.7	44.7	44.4	44.7
Home size	3.07	3.71	3.21	3.41

Notes: The homeownership rate is defined as the fraction of all homeowners in the population. The home size is defined as the average home size (in terms of the numeraire consumption good) of all homeowners.

Table 3.4: The effect of employer contributions

	Employers match workers' deposits by					
	0 pct	20 pct	40 pct	60 pct	80 pct	100 pct
Homeownership rate	44.7	44.7	44.9	44.8	47.1	47.1
Home size	3.71	3.72	3.75	3.96	4.06	4.10

Notes: See Table 3.3. This table shows results that allow employers to contribute to workers' HPF savings according to some percentage.
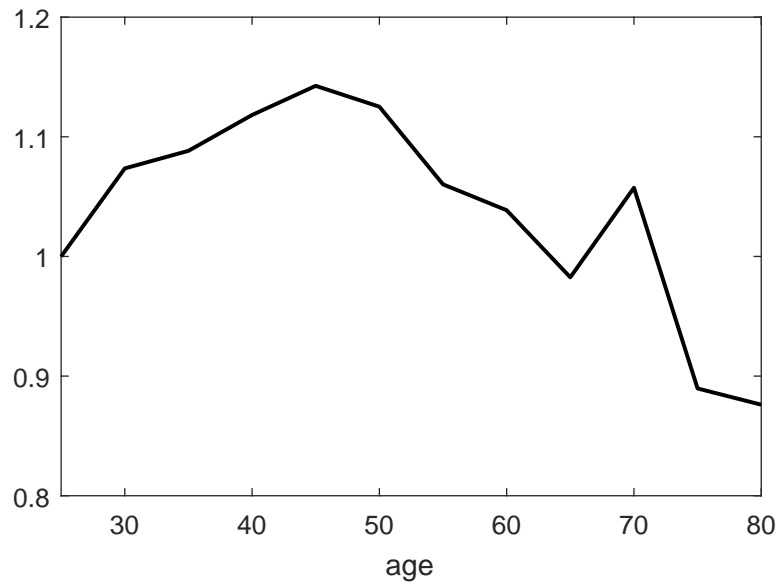
Figure 3.1: Household income by age, China 1998-2002

Source: Chinese Household Income Project Series 2002. Income for the age group 20-25 is normalized to 1.
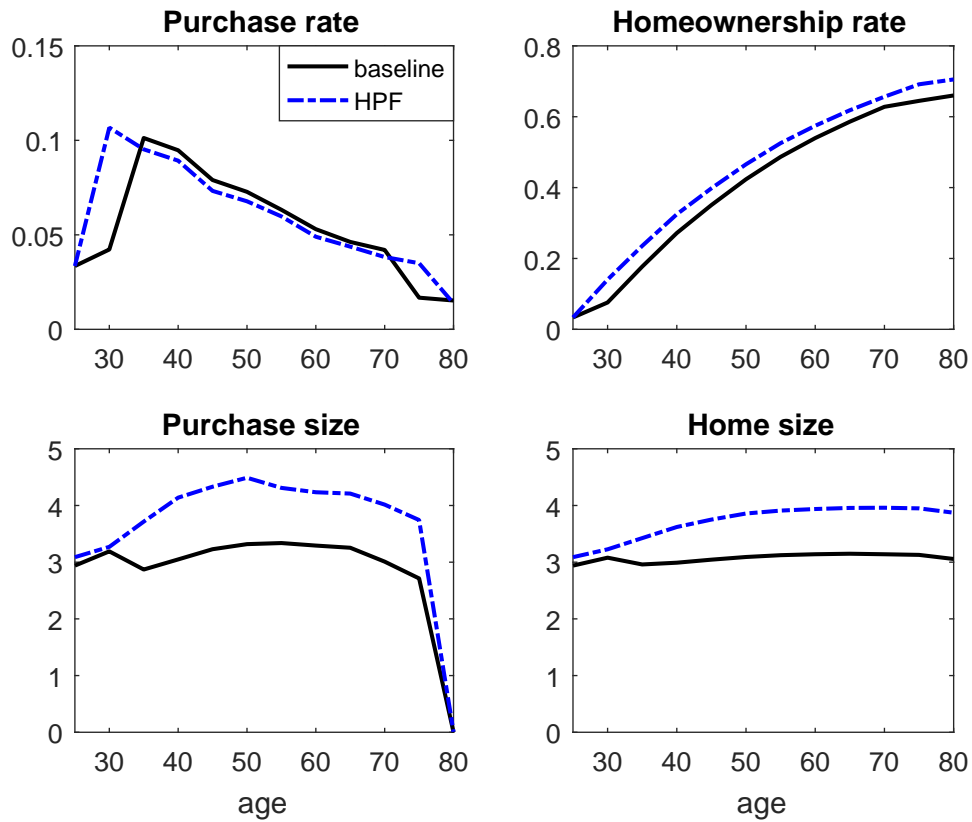
Figure 3.2: The impact of the HPF program

Notes: Simulations based on the baseline model and based on the HPF program. The purchase rate is defined as the fraction of homebuyers (or the fraction of new homeowners) in the population. The homeownership rate is defined as the fraction of all homeowners in the population. The purchase size is defined as the average size of new homes purchased (in terms of the numeraire consumption good). The home size is defined as the average home size of all homeowners.
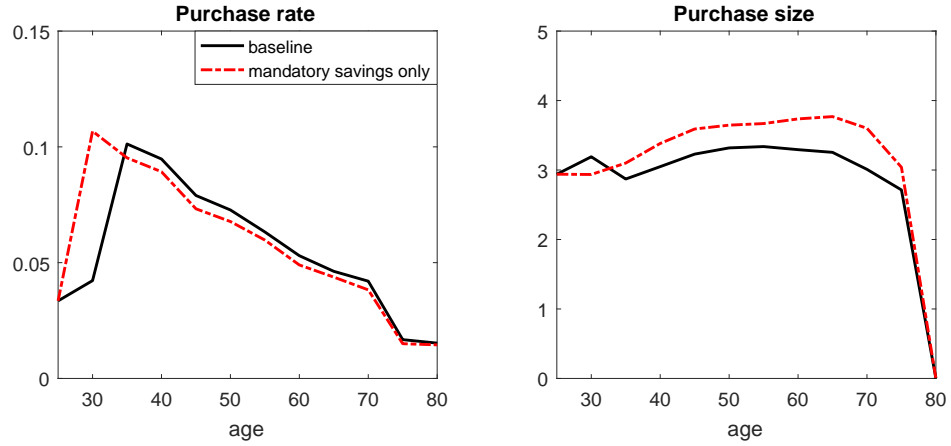
Figure 3.3: The effect of the mandatory-savings feature

Notes: See Figure 3.2.
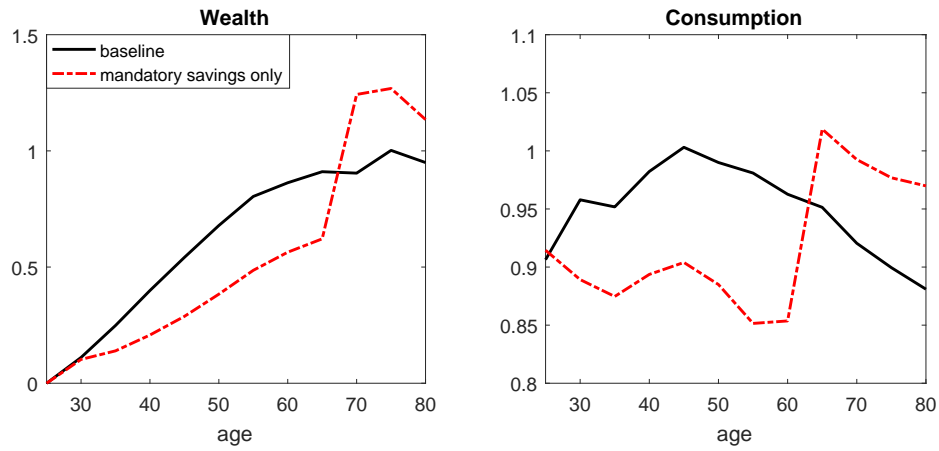
Figure 3.4: Consumption and wealth under mandatory savings

Notes: Wealth is defined as the sum of liquid savings and the value of one's home. Consumption refers to non-housing consumption.
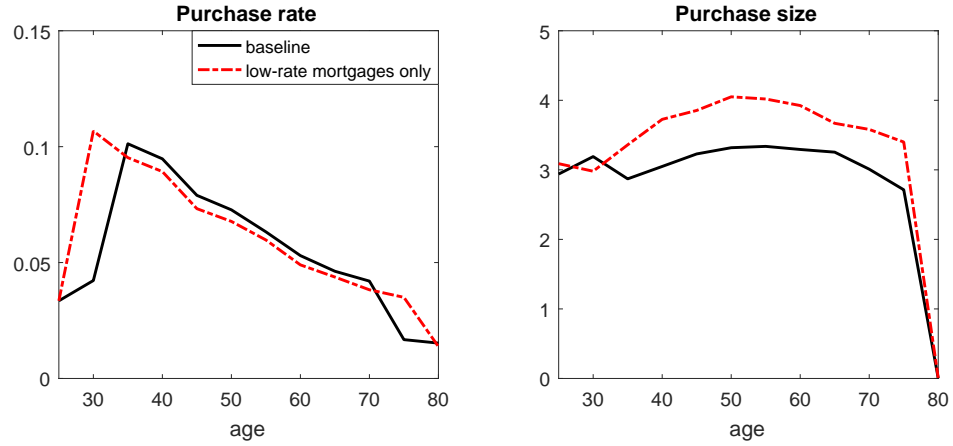
Figure 3.5: The effect of the below-market rate mortgage feature
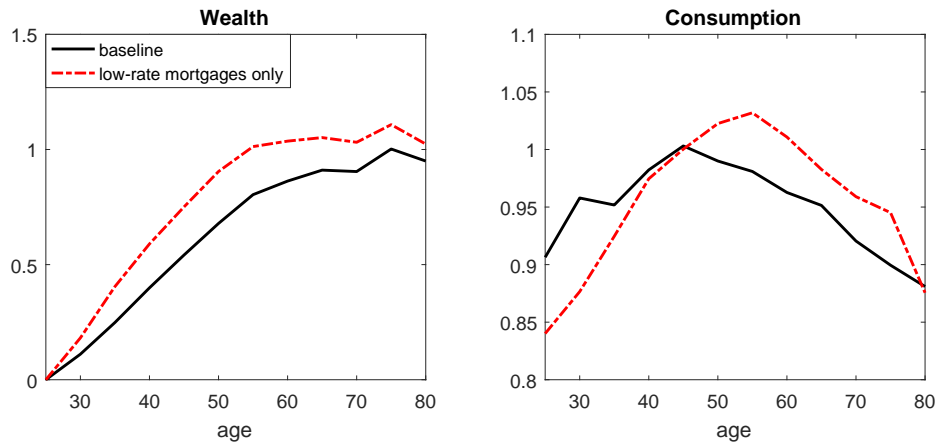
Notes: See Figure 3.2.

Figure 3.6: Consumption and wealth under below-market rate mortgages
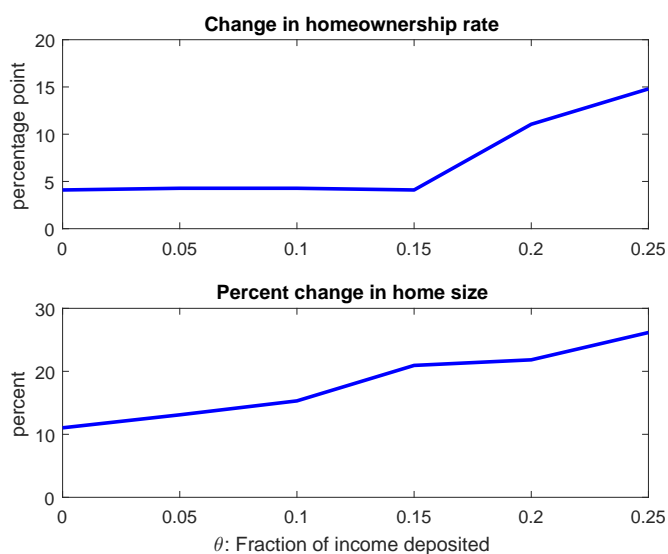
Notes: See Figure 3.4.

Figure 3.7: The effect of the fraction θ of income deposited into the HPF

Notes: This figure illustrates the change in the homeownership rate and the percent change in the average home size relative to the baseline model, generated by housing programs with a mortgage rate of 2 percent below the market rate.
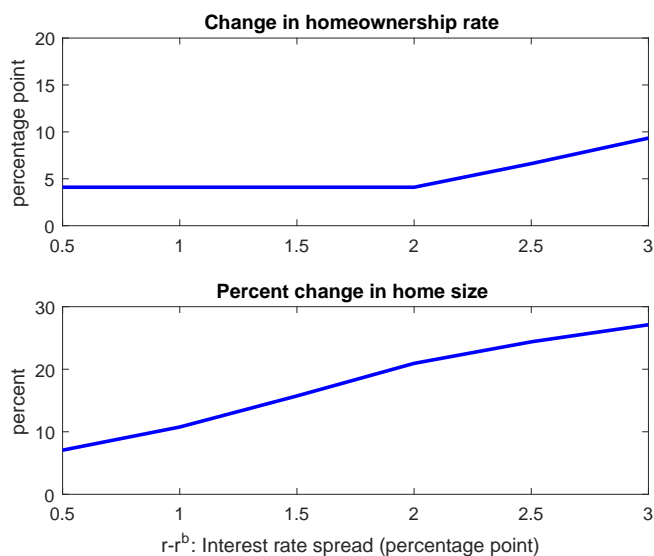

Figure 3.8: The effect of the mortgage rate spread

Notes: This figure illustrates the change in the homeownership rate and the percent change in the average home size relative to the baseline model, generated by housing programs with $\theta = 0.15$.
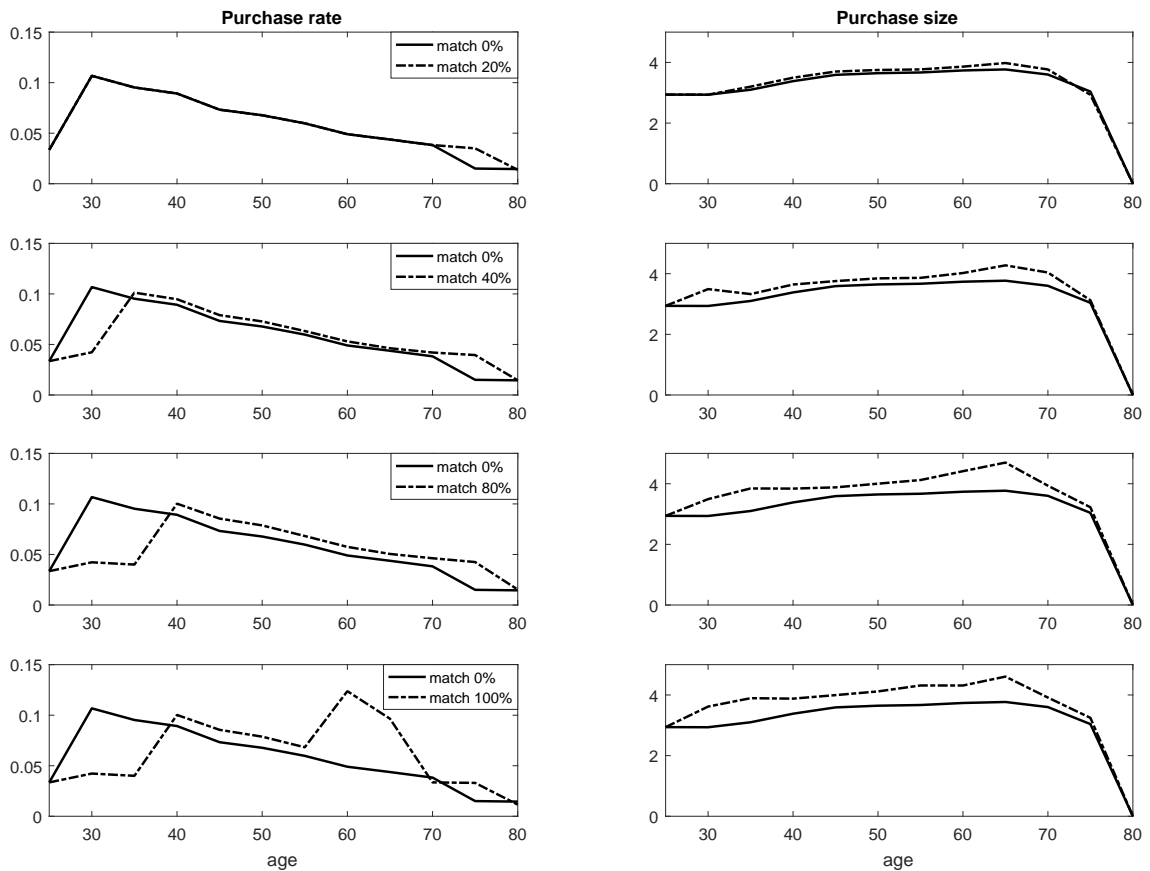
Figure 3.9: The effect of employer contributions under a mandatory-savings-only program

Notes: This figure illustrates the purchase rate and the average purchase size generated by housing programs with a mandatory fraction of income deposited, $\theta = 0.15$, and an $x\%$ matching contribution from the employer.
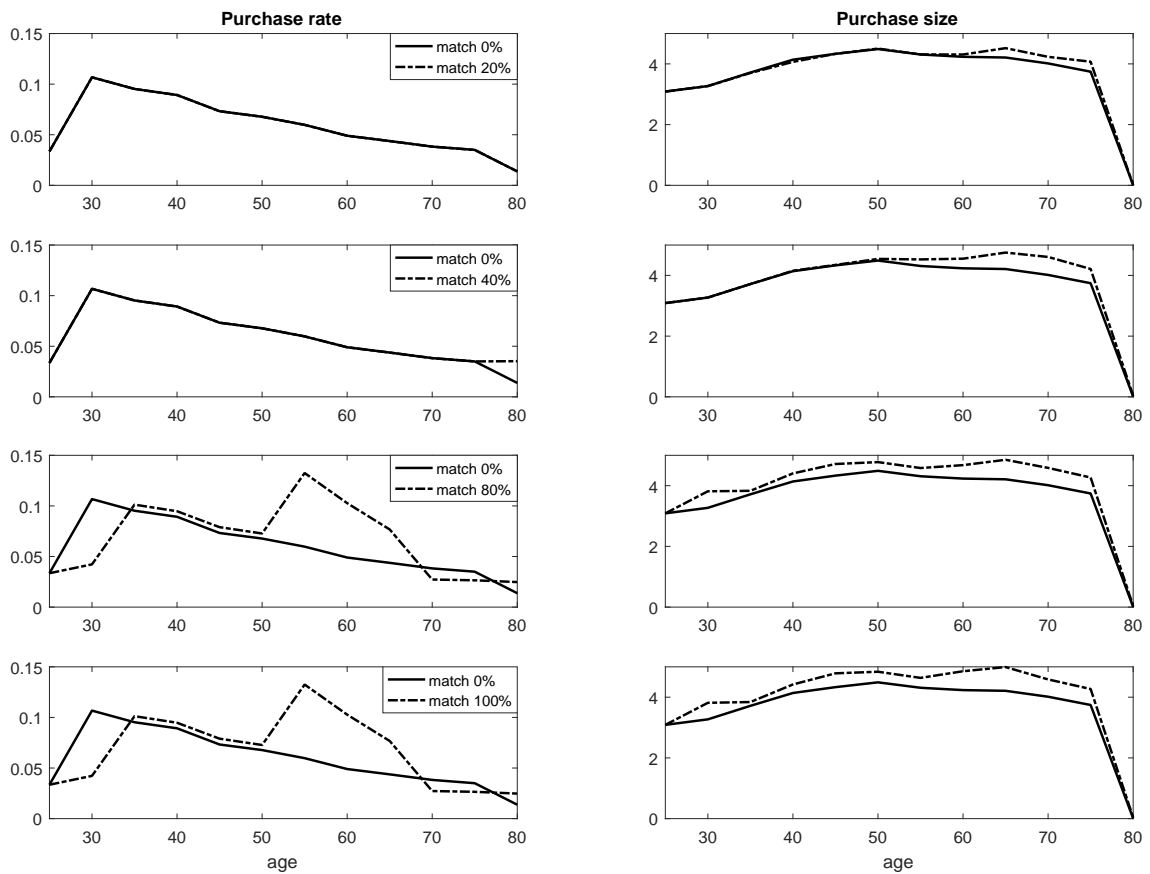
Figure 3.10: The effect of employer contributions in the HPF program

Notes: This figure illustrates the purchase rate and the average purchase size generated by housing programs with a mandatory fraction of income deposited, $\theta = 0.15$, and an $x\%$ matching contribution from the employer. In addition, the program offers mortgages at a rate of 2 percent below the market rate.

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APPENDIX A

Home Equity Extraction and the Boom-Bust Cycle in Consumption and Residential Investment

A.1 Additional Empirical Evidence

A.1.1 Equity Extraction and Household Expenditures, 2005-2013

Table A.1 shows the results from estimating Equation (1.2) using the expanded PSID expenditure data, 2005-2013. Non-housing expenditures include food, transportation, education, childcare, health, telephone and internet, furniture, cloth, recreation and trips. Housing expenditures include property tax, insurance, utilities, home improvement, regular maintenance and repair, and mortgage payment. The difference in total expenditure growth between extractors and non-extractors is mainly explained by the difference in the housing expenditure growth, consistent with the results in Table 1.6.

Table A.1: Equity extraction and expenditure growth, 2005-2013

	Total	Nonhousing	Housing	Excl. mort.	Improv.
$I(Extract)_{i,t}$	0.101	0.006	0.095	0.045	0.037
	(0.022)	(0.009)	(0.019)	(0.013)	(0.010)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	5,817	5,817	5,817	5,817	5,817
Expenditure Share	1.00	0.59	0.41	0.21	0.06

Notes: Sample period: 2005-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

A.1.2 Spending of a marginal dollar extracted from home equity

I estimate the following specification to obtain the spending pattern on a marginal dollar extracted.

$$\triangle c_{i,t}^k = \beta_0 + \beta_1 \triangle b_{i,t} + X_{i,t}\beta_2 + W_{i,t-1}\beta_3 + \gamma_t + \varepsilon_{i,t} \tag{A.1}$$

where $\triangle c_{i,t}^k$ is the dollar change in expenditure category k (total, housing, non-housing), and $\triangle b_{i,t}$ denotes the change in the total mortgage balance. All dollar amounts are converted to 2009 dollars. Other variables are defined as in Equation (1.2).

The results in Tables A.2 and A.3 are consistent with those in Tables 1.6 and 1.7, showing that spending of a marginal dollar on housing accounts for the dominate share in the total spending of the dollar, and this fraction is largest among young homeowners.

Table A.2: Spending of a marginal dollar extracted from home equity

| | Dollar change in | | | | |
	Total	Nonhousing	Housing	Excl. mort.	Improv.
$\triangle b_{i,t}$	0.061	0.008	0.053	0.037	0.037
	(0.029)	(0.006)	(0.028)	(0.017)	(0.016)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	9,606	9,606	9,606	9,606	9,606

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

Table A.3: Housing expenditures out of a marginal dollar from home equity, by age

| | Dollar change in housing expenditures | | | | |
	22-30	31-45	46-55	56-65	65+
$\triangle b_{i,t}$	0.208	0.080	0.074	0.050	-0.443
	(0.078)	(0.039)	(0.021)	(0.019)	(0.483)
Controls	Y	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y	Y
# Obs.	309	3,340	3,278	1,987	692

Notes: Sample period: 1999-2013. Estimation method: Pooled OLS. Standard errors are clustered at household level. Control variables are the same as in column (4), Table 1.4.

A.1.3 Instrumenting with MSA Housing Supply Elasticities

This section describes the estimation strategy and the results by using the second set of instruments, MSA level housing supply elasticities developed by Saiz (2010), to estimate the effect of house price shocks on equity extraction. This set of instruments measures the amount of developable land in metropolitan areas from satellite-generated data on terrain elevation and presence of water bodies. For example, Miami, Los Angeles, San Francisco,

and San Diego have the lowest housing supply elasticity among 255 measured MSAs. The identification assumption is that housing supply side conditions are not affected by individual household equity extraction decisions.

Since housing supply elasticities are time-invariant, I use cross-sectional variations by estimating the extraction response in specific years. In the first stage, I estimate

$$\triangle hp_{i,t} = \delta_{0,t} + \delta_{1,t} S E_m + \delta_{2,t} \triangle y_{i,t} + W_{i,t-1} \delta_{3,t} + v_{i,t}, \quad t = 2001, 2003, ..., 2013. \quad (A.2)$$

where $S E_m$ is the housing supply elasticity in MSA m. The rest of variables are defined as in Equation (1.3) The second stage has the same specification as in Equation (1.5).

Table A.4 illustrates the prediction from the 1st stage. It shows that the housing supply elasticity is a strong predictor of the change in self-reported home value during the boom period from 2001 to 2007, whereas in the bust year 2009, MSAs in the most inelastic supply areas experienced the largest home value decline. Patterns in 2011 and 2013 are similar to 2009 (not shown in the table).

Table A.5 shows the 2SLS estimation results by year. The first stage coefficient on housing supply elasticity is negative during 2001-2007, as implied by Table A.4. The second stage shows that during the boom period, house price shocks caused a large increase in the home equity extraction rate. In the bust year 2009, and similarly in 2011 and 2013 (not shown in the table), homeowners in low supply elasticity areas still extract home equity, which can be explained by the consumption smoothing motive discussed in Hurst and Stafford (2004).[1] Due to the small sample size after matching households with their MSA and with available MSA housing supply elasticities, I do not perform the cross-age-group estimation.

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[1] As pointed by Bhutta and Keys (2016), during the bust years, house prices fell in all geographical locations. So, it is not right to argue that households in the less depressed housing market locations are more likely to extract equity.

Table A.4: Housing supply elasticity and home value growth

SE_m quartile	Self-reported home value growth				
	2001	2003	2005	2007	2009
1st (Boston, Chicago, Jersey City Los Angeles, San Diego, Seattle, etc.)	.172	.184	.301	.110	-.166
2nd (Baltimore, Charleston, Detroit, Denver, Minneapolis, etc.)	.100	.136	.185	.152	-.142
3rd (Dallas, St.Louis, Toledo, Philadelphia, etc.)	.053	.085	.150	.104	-.038
4th (Indianapolis, Des Monies, Richmond, Jackson, etc.)	.038	.056	.030	.020	-.052
# Obs.	889	942	952	978	1,062

Notes: This table shows the average PSID family self-reported home value growth in each housing supply elasticity quartile.

Table A.5: Equity extraction and house price shocks, 2SLS with MSA housing supply elasticities

	2001		2003		2005		2007		2009	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
	$\triangle hp$	I(Ex)	$\triangle hp$	I(Ex)	$\triangle hp$	I(Ex)	$\triangle hp$	I(Ex)	$\triangle hp$	I(Ex)
SE_m	-.035		-.045		-.099		-.050		.047	
	(.011)		(.009)		(.011)		(.009)		(.008)	
$\widehat{\triangle hp}$		-.234		-.001		.469		.528		-.645
		(.366)		(.360)		(.160)		(.300)		(.317)
F-stat	4.47		6.12		17.21		6.68		22.24	
# Obs.	889	889	942	942	952	952	978	978	1,062	1,062

Notes: This table shows the results from estimating Equation (A.2) and (1.5). Methods: 2SLS by year. Standard errors are clustered at MSA level.

A.2 Numerical Solution Methods

In this section, I describe the two-step numerical procedure used to solve the model. I assume the aggregate state, $S \equiv (p, p^I, r^b)$, is set at the steady state value. In the first step, I solve value functions over a fixed-grid state space. In the second step, given the realized state, I solve the optimal choices over a denser choice set, by applying the linear interpolation technique to compute the continuation value.[2]

To obtain value functions, I discretize the state space (h, b, a, y). I choose 20 grids for each of the endogenous state variables: h, b and a. For the stochastic component of y, I use the method introduced by Tauchen (1986) to discretize an AR(1) process to 5 realizations. Tauchen's method chooses grid points and computes the corresponding transitional probability matrix.

I use the following algorithm to solve value functions in the first step. First, the end value is pinned down by the bequest function. Second, in each period j back to the initial, given each possible state (h, b, a, y), I compute $V_j^C(h, b, a, y)$ and $V_j^N(h, b, a, y)$, respectively. To obtain $V_j^C(h, b, a, y)$, I construct a choice set $\{h_C'(h, b, a, y), b_C'(h, b, a, y), a_C'(h, b, a, y)\}$. The choice set taking all constraints in Problem (1.6) into account may vary across states. The choices are spaced more closely to the constraints of h_C' and b_C'. Third, I compute the value of the objective function as in Problem (1.6) for each choice, by applying the linear interpolation technique to compute the continuation value if the choice is not on the grid points. Fourth, I compare the value of the objective function across all choices, and set $V_j^C(h, b, a, y)$ to the largest value. Fifth, I follow the same procedure to obtain $V_j^N(h, b, a, y)$, and set $V_j(h, b, a, y) = \max\{V_j^C(h, b, a, y), V_j^N(h, b, a, y)\}$

To obtain optimal choices in the second step, given a realized state (h, b, a, y), I solve the optimization problem as described in step 2-5 above by searching over a denser choice set, which allows me to find the solution more precisely. To obtain impact responses after a permanent shock, I fix the individual-specific state (h, b, a, y) at the beginning of the shock period at the same value as in the original steady state, and solve the value functions and optimal choices under the shock value. To obtain the aggregate response, I average responses across households of the same age, and then average across ages by assuming equal population.

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[2]I experimented with alternative interpolation methods, such as the Chebyshev polynomial approximation. Since these methods are designed to approximate smooth functions using smooth functions, the approximation performance is poor especially at the boundary of the state space, because value functions in my model are not smooth.